Essays in Behavioural Economics

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Thesis

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Declaration

This thesis is submitted to the University of Warwick in accordance with the requirements of the degree of Doctor of Philosophy in Economics. I declare that it has not been submitted for a degree at another university. Chapter 1 is co-authored with David Ronayne (ESMT Berlin) and Daniel Sgroi (University of Warwick). Chapter 2 is co-authored with Daniel, Elliott Ash (ETH Zurich) and Shi Zhuo (University of Warwick). Chapter 3 is co-authored with Daniel, Emmanouil Benetos (Queen Mary University) and Alessandro Ragano (University College Dublin).

Abstract

This thesis is a collection of three essays in behavioural economics. The first paper considers one of the most well-known cognitive biases (the "sunk cost effect"). Given its notoriety, it is perhaps somewhat surprising that there has not been many lab-based experiments that try to measure the effect. In our design we find evidence of a significant sunk cost effect (23% of the sample were subject to it) and are able to trace its determinants back to a particular aspect of intelligence ("cognitive reflection"). Moreover, we use our found sunk cost behaviour to validate a new off-the-shelf scale (the "SCE-8") for researchers to use.

The second paper then considers how a particular type of mental training ("mindfulness meditation") can alleviate a different type of cognitive bias ("information avoidance"). Reporting evidence from a randomised-controlled trial we find that a short mindfulness treatment (two weeks, 15-minutes a day) is able to significantly reduce information avoidance in comparison to the control group. Since anyone in the population can vary in their levels of mindfulness (even if they have never meditated), these results potentially have a wide relevance. Possible mechanisms and policy implications are discussed.

Finally, the third paper takes a step back from individual cognitive biases to investigate a novel way of measuring wellbeing at the macro (national) level. It asks whether the emotions of a country's most popular songs potentially carries a signal of how happy people are actually feeling in the population. Applying emotion-detecting machine learning algorithms to the UK's chart music, we find that the valence of the most popular song of the year can reliably predict how happy people are (with respect to the leading survey-based measure of life satisfaction).

Evaluating the Sunk Cost Effect*

David Ronayne,[†] Daniel Sgroi,[‡] Anthony Tuckwell[§¶]

Abstract

We provide experimental evidence of behavior consistent with the sunk cost effect. Subjects who earned a lottery via a real-effort task were given an opportunity to switch to a dominant lottery; 23% chose to stick with their dominated lottery. The endowment effect accounts for roughly only one third of the effect. Subjects' capacity for cognitive reflection is a significant determinant of sunk cost behavior. We also find stocks of knowledge or experience (crystallized intelligence) predict sunk cost behavior, rather than algorithmic thinking (fluid intelligence) or the personality trait of openness. We construct and validate a scale, the "SCE-8", which encompasses many resources individuals can spend, and offers researchers an efficient way to measure susceptibility to the sunk cost effect. *JEL: D91, C83, C90*

Keywords: sunk cost effect, sunk cost fallacy, endowment effect, cognitive ability, fluid intelligence, crystallized intelligence, reflective thinking, randomized controlled trial, online experiment, online survey, psychological scales, scale validation, Raven's progressive matrices, international cognitive ability resource, cognitive reflection test, openness.

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¶***My Contribution:*** Contribution to this paper was shared equally among the co-authors. Tuckwell helped with the empirical design, programmed and ran the pilots and experiments, analysed the results and contributed to the writing and revisions.

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"No matter how far you've gone down the wrong road, turn back."

- Turkish proverb

1 Introduction

In a famous example by Thaler (1980), an individual who purchased a $40 ticket to a basketball game finds themselves driving for miles through a snowstorm, just because they feel it would be wasteful to ignore the initial investment. A seminal definition of this "sunk cost fallacy" or "sunk cost effect" by Arkes and Blumer (1985) characterizes individuals as falling prey to the effect when they continue an endeavor as a result of previously invested resources such as time, money, or effort. Many definitions have been offered, but central to them all is the idea that some actions (sunk) in the past constrain decision-making in the present despite the fact that the actions do not affect the attractiveness of the available options. The effect seems ubiquitous, with work showing that it is even present in mice and rats (Sweis et al., 2018). It is also an important part of the work by Thaler (1999) on mental accounting, which is based on the idea that individuals often fail to treat money as a fully fungible resource. We offer contributions to the identification, understanding, and measurement of the sunk cost effect in humans.

First, we conduct an experiment with pecuniary incentives to detect behavior consistent with the sunk cost effect in a controlled setting. Subjects in the primary treatment completed a real-effort task to earn a lottery. Subjects who earned the lottery ($n = 268$) then had the (unanticipated) choice to switch to a dominant lottery; 23% chose to stick with their earned (and dominated) lottery. We argue that the endowment effect is an intrinsic part of the sunk cost effect. To uncover how large a part, we ran a second treatment in which subjects ($n = 197$) did not face the effort task, but were instead endowed with the inferior lottery before having the choice to switch to the superior lottery; 7% chose to stick with their endowed (and dominated) lottery.

Second, we document correlations between sunk cost behavior and different traits that have been argued to be related to the effect, which we pre-registered in advance.[1] One type of cognitive ability introduced by Frederick (2005), "cognitive reflection", concerns the ability of an individual to override a heuristically-primed ("System 1") response and engage in further deliberate ("System 2") reflection to figure out the correct answer, and has been found to be predictive of various types of biases (Toplak et al., 2011).[2] We test its capacity to explain our behavioral measure of the sunk cost effect and find it to be a highly significant predictor. Because cognitive reflection is itself likely to be a function of different aspects of intelligence and thinking style (Stanovich and West, 2008) we also test three of these measures and find crystallized intelligence to be a significant driver.

[1]In our pre-trial registration (https://doi.org/10.1257/rct.4083-2.0) we listed a small number of variables linked to cognitive ability, which have been argued to be related to the sunk-cost effect. We did this both to test the associations posited in the literature, and to limit our ability to find and exploit spurious correlations.

[2]Terms "System 1" and "System 2" are those famously used by Kahneman (2011).

Third, we validate a scale comprised of hypothetical scenarios to measure individuals' susceptibility to the sunk cost effect. Using factor analysis, we refine the scale down from 18 to 8 scenarios; the *SCE-8*. We find that our SCE-8 measure emulates the behavioral measure generated by our experiment well. This suggests the SCE-8 may adequately measure subjects' susceptibility to the sunk cost effect in lieu of a behavioral measure. As such, we offer our scale as a simpler and more cost-effective way to capture subjects' susceptibility to the effect.

Fourth, to reflect the wide-ranging nature of the effect we include multiple types of sunk resources including effort, time, money and emotional attachment. Effort and time are perhaps the most relevant costs in our experiment, but all four are represented in the SCE-8. Our results indicate that many different sunk resources contribute to a singular, underlying sunk cost effect.

We also provide a definition of the sunk cost effect and contrast it with the endowment effect. Given the tight structure of our definition it is also possible to distinguish between the sunk cost effect and the sunk cost fallacy, which until now many have used interchangeably.

2 Literature

Many papers report evidence of behavior consistent with the sunk cost effect. These studies typically rely on responses to hypothetical questions, are subject to various confounds, or are field experiments that tend to suffer from real-world factors that complicate the interpretation of the effect. For example, it can be hard to disentangle the sunk cost effect from other possible reasons for behavior in real world situations involving price data (Ashraf et al., 2010; Berry et al., 2020; Cohen et al., 2015), while consumer goods may be subject to heterogeneous mental accounting (Arkes and Blumer, 1985; Just and Wansink, 2011), and penny auctions can suffer from intractable bidding environments (Augenblick, 2016). In contrast, lab and online experiments offer greater control and cleaner measurement; attractive merits for our purposes.

Some experiments have attempted to identify the sunk cost effect. Friedman et al. (2007) find limited evidence of the effect, but with a design that does not give subjects a choice between actions, an important factor in generating the effect (Staw, 1976). The design of Weigel (2018) features choice but employs a penny auction task, the dynamic nature of which raises the need to control for confounds such as the gambler's fallacy.[3] In contrast, we conduct an experiment with a simple structure in which subjects sink resources then make a one-off decision.

Several papers have tested the role of cognition in accounting for sunk cost behavior.[4] Evidence has been mixed, with often a small or insignificant correlation found between intelligence measures and sunk costs. However, the majority of studies measure sunk cost behavior using unvalidated hypothetical scenarios e.g., Bruine de Bruin et al. (2007); Larrick et al. (1993); Parker

[3]The lab experiment of Haita-Falah (2017) is a second design allowing for choice, but the task and instructions are complex and there is evidence subjects may not understand the task (see e.g., Weigel, 2018, footnote 3).

[4]A more general drive in economics has examined the relationship of cognitive ability to other important characteristics e.g., temporal and risk preferences (Dohmen et al., 2010) and cooperation (Proto et al., 2019).

and Fischhoff (2005); Stanovich and West (2008); Strough et al. (2008); Toplak et al. (2011). We incentivize subjects to sink resources via a real-effort task and find evidence that cognitive reflection and crystallized intelligence measures significantly explain the variation in our data.

Early in the study of the sunk cost effect, there were discussions of the extent to which non-monetary resources might be fungible. For instance, Thaler (1999) briefly discusses how people appear to allocate time sub-optimally, while Soman (2001) argues people treat sunk time and sunk money differently. However, there have been almost no attempts within the literature to explore the commensurability of time, effort, money or emotional attachment as separate factors in a sunk cost problem. This might be considered important especially if these concepts cannot be converted readily into monetary values (Leclerc et al., 1995). We include different resources in our scale (time, money, effort, and emotion) and find them all to be relevant in describing a single underlying factor: susceptibility to the sunk cost effect.

When considering the role of cognition in explaining behavioral biases, it is important to distinguish between different measures. Cognitive reflection is a type of cognitive ability introduced by Frederick (2005) relating to the ability to override a heuristically-primed or knee-jerk response and engage in further reflection to figure out a correct answer, and has been found to predict various types of bias (Toplak et al., 2011). We test its potential to explain the sunk cost effect using our behavioral and scale measures, and find it highly predictive of both. An individual's cognitive reflection, in turn, is likely dependent on other aspects of intelligence and thinking style (Stanovich and West, 2008; Stanovich, 2012). In particular, accumulated stocks of knowledge and experience that might help one to recognize the need to override an instinctive response (crystallized intelligence) and styles of thinking conducive to discovering new perspectives on a problem (open-minded thinking).[5] Interestingly, the literature identifies fluid intelligence (the ability to think logically or algorithmically, as measured by various I.Q. tests) as having less of a role, because the computational power required to override an impulsive response is often only very slight (Stanovich, 2008): what matters is recognizing the need to override it in the first place. Our results support this hypothesis in the context of sunk costs.

Our paper is the first to validate a scale composed of hypothetical scenarios to measure the sunk cost effect. The effect is not currently measured by any widely accepted scale. It evades, e.g., the "Big 5" personality inventory (Costa and McCrae, 1989). As one of the most widely known behavioral biases, it seems important to have a reliable yet easy to use scale to measure susceptibility to the effect. To this end, we offer our SCE-8 scale to researchers for any study in which the sunk cost effect may explain outcomes, reducing or eliminating the need to run a full experiment. Collecting SCE-8 data would allow susceptibility to the effect to be measured and used in the same way as other common items including risk tolerance (Blais and Weber, 2006), patience levels (Brockhoff et al., 2015), and personality measures (Costa and McCrae, 1989).

[5] A related concept to open-minded thinking is that of mindfulness: Hafenbrack et al. (2014) find that both trait mindfulness and mindful states induced through meditation increase resistance to the sunk-cost effect.

3 Design

Our design combines a randomized experiment, a scale composed of hypothetical questions, and trait measures that have been linked to susceptibility to the sunk cost effect. We organize and structure our approach around a definition of the sunk cost effect, which we detail now.

3.1 The sunk cost and endowment effects

If an individual has sunk resources *positively associated* with an alternative, and chooses that alternative, but would not have chosen it if no such resources were sunk, we define them as exhibiting the sunk cost effect. More formally, consider a binary choice set $\{X, Y\}$ and a quantity of resources $r \geq 0$ sunk in ways positively associated with X, where r does not directly affect the utility garnered from either X or Y, and let $C_i(\{X, Y\}; r)$ be i's choice function. Under our definition, i exhibits the sunk cost effect when $r > 0$, $C_i(\{X, Y\}; r) = X$, and $C_i(\{X, Y\}; 0) = Y$.[6,7]

Within the definition of the sunk cost effect, the term "positively associated" is deliberately general, to reflect the diverse range of contexts across which the effect applies. A simple example may be the money spent on (and hence positively associated with) a theater ticket; a more complex one may be the various resources sunk into (and hence positively associated with) developing previous stages of an ongoing project. We are also agnostic about what might count as a cost and our hypothetical scenarios cover several: effort, time, money, and emotion.

What distinguishes the sunk cost effect from the endowment effect (Kahneman et al., 1990) is that the former requires *some* resources to be sunk. In contrast, the latter occurs when an individual receives an endowment costlessly, deriving value from the very fact they have it. The sunk cost effect is thereby more nuanced, specifying that the individual must have spent (sunk) some resources to have the "endowment". As such, we view the endowment effect as an essential and necessary part of the sunk cost effect: when an individual exhibits the sunk cost effect they also exhibit the endowment effect, but the reverse is not necessarily true.

To detect the part of the sunk cost effect net of the endowment effect (and hence the existence of the sunk cost effect in its own right), we dedicate a treatment group to measuring the latter. By comparing responses there to those in our primary sunk cost group, we can identify whether sunk costs have an effect over and above the otherwise standard endowment effect.

[6] Moreover, if this is true *and* i believes X yields higher utility we say that i exhibits the sunk cost *fallacy*, which is therefore a subset of the effect. Our definitions imply that within mainstream economics, the effect and fallacy are identical as $C_i(X, Y) = X$ typically implies that i believes $U_i(X) > U_i(Y)$, where U_i is $i's$ utility function. This may explain why the two terms are often used interchangeably. Our definitions otherwise serve to label the choice outcome as the effect and the beliefs supporting that outcome as the fallacy. Others have also drawn distinctions between the terms but without explicit mention of payoffs or beliefs, e.g., Olivola (2018) remarks that the fallacy refers to taking an inferior action due to sunk costs whereas the effect refers only to taking a different action.

[7] A related and older term is the "Concorde effect" (Dawkins and Carlisle, 1976), named after the sustained investment in the Concorde supersonic jet project, after it was recognized to be an unprofitable venture.

3.2 Experiment

Subjects. Subjects were recruited via the Amazon Mechanical Turk (MTurk) online platform, commonly used throughout the social sciences including economics (e.g., DellaVigna and Pope, 2017; Kuziemko et al., 2015). MTurk's population has been shown to be more demographically diverse and to produce data of a comparable quality to some more traditional participant pools (Chandler et al., 2014; Paolacci and Chandler, 2014), with many studies replicating classic experiments across various domains including cognitive psychology (e.g., Goodman et al., 2013; Paolacci et al., 2010) and economics (e.g., Horton et al., 2011). The software Qualtrics was used to perform the experiment. We restricted participation to those in the US, with a good track record (at least 95% of MTurk jobs approved), at least some experience (successfully completed at least 50 MTurk jobs), and who had not taken part in any of our pilots.

Pre-trial registration. The experiment was registered in advance in the AEA RCT Registry (Ronayne et al., 2019). There, we provided an experimental design, power calculations, and detailed our intention to study: reflective thinking as captured by the Cognitive Reflection Test; fluid and crystallized intelligence captured by Raven's progressive matrices and the verbal reasoning item of the International Cognitive Ability Resource, respectively; the Openness scale from the Big Five Personality Inventory; and various demographics. All these measures are included in our analysis, and no other measures were pre-registered.

Design overview. Our design involved one wave of data collection from 528 subjects.[8] Subjects were randomly allocated to one of three groups such that approximately 60% and 35% fell into our primary and secondary treatment groups, with 5% in the final group.

In the primary *sunk cost* group, subjects completed a real-effort task (counting letters in blocks of text composed of Latin words). If they did well, they earned a lottery (termed an "asset" for subjects) paying \$10 with a 10% chance (else \$0), before being given an (unanticipated) choice to switch to a dominant lottery paying \$10 with a 20% chance (else \$0). The \$1 difference in expected payoff corresponds to 25% of the subjects' participation fee, and represents a meaningful amount to the MTurk population, who regularly respond to similar stakes. We detail the task below, but the essential idea is that the effort, time, etc. exerted to obtain the lottery in the task form a sunk resource, $r > 0$, positively associated with it, which, if susceptible to the sunk cost effect, leads an individual to a different choice (the inferior lottery) to that if they had spent no such resources (the superior lottery).

In the *endowment* group, subjects did not complete the real-effort task to earn the asset. Instead, these subjects were endowed with the inferior (10% chance of \$10) lottery before facing the same (unanticipated) choice to switch to the dominant (20% chance of \$10) lottery.

[8]Calculations suggested this adequate to detect effects with 80% power and 5% significance (Ronayne et al., 2019).

The third and final group was run to check that subjects could generally be expected to maximize their expected pecuniary outcome and understood the wording and descriptions of the lotteries. Subjects in this condition did not face any real-effort task and were not endowed with anything. They were simply given a straight choice between the two lotteries.

After their group-specific tasks, all subjects completed a set of psychometric measures. First, 18 hypothetical scenarios (presented in a random order) which they responded to via a 6-point Likert scale (see Appendix A-C for the numbered list). These scenarios form the basis of the scale we set out to validate and were drawn from various sources: numbers 1-10 are from the Health and Retirement Study[9]; 11-12 are based on Arkes and Blumer (1985); and 13 is based on Thaler (1980). The final scenarios (14-18) we created to balance the set across different types of sunk resources . Table 1 describes which scenarios highlight which resources: *effort*, *time*, *money*, *emotion*, and a final category *belief*, shorthand for the resources sunk during the process of belief formation, which is likely to be a subset of effort.

Table 1: Different types of sunk resources highlighted by the hypothetical scenarios

Resource	Scenario ID																	
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Effort		✓	✓	✓		✓			✓	✓					✓	✓	✓	
Time		✓	✓	✓					✓		✓			✓	✓	✓		
Money	✓				✓		✓	✓				✓	✓					✓
Emotion	✓					✓								✓				
Belief															✓	✓	✓	

The full text of the 18 scenarios is given in the redacted transcript in Appendix A-C. A dark tick indicates the scenario's primary focus, while lighter ticks indicate some secondary resources.

Subjects then completed the Cognitive Reflection Test (CRT), measures of fluid and crystallized intelligence, and openness to experience. The CRT measures reflective capacity, i.e., the ability to think about problems that tend to induce people to fall prey to a behavioral bias (Frederick, 2005). We adopt the extended version of the test (Toplak et al., 2014), which consists of 7 right/wrong questions, giving each subject a score in $\{0, \ldots, 7\}$.

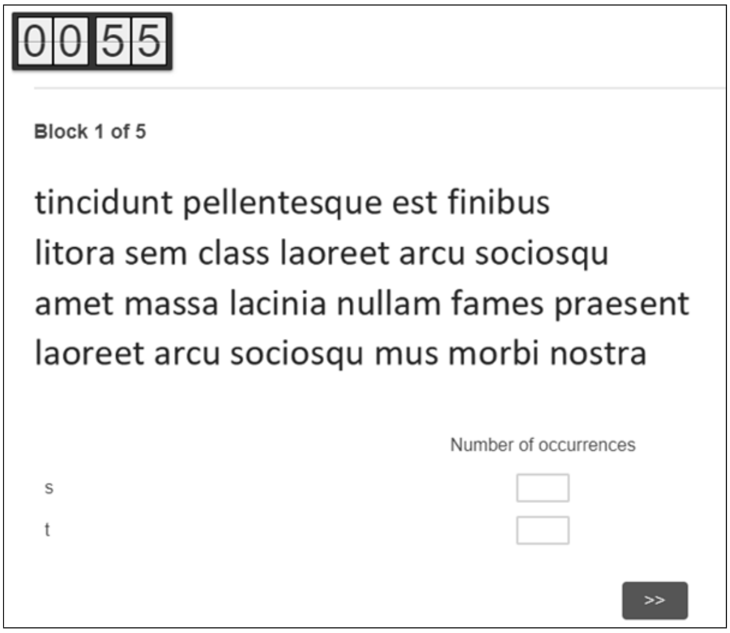
Fluid intelligence was measured using 10 Raven's progressive matrices (John and Raven, 2003), giving scores $\{0, \ldots, 10\}$. We follow the common practice of assessing crystallized intelligence by verbal reasoning ability (e.g., Bruine de Bruin et al., 2007) and use the 16-item verbal reasoning subset of the International Cognitive Ability Resource (ICAR) (Condon and Revelle, 2014), giving scores $\{0, \ldots, 16\}$. Potential for open-minded thinking was gauged via the openness to experience personality trait, which we measured using a 12-item sub-scale from the NEO Five Factor Inventory (Costa and McCrae, 1989); each item is responded to via a 5-point Likert scale coded $\{0, \ldots, 4\}$, giving scores $\{0, \ldots, 48\}$.

[9] https://hrs.isr.umich.edu/about

The measures were incentivized such one of each subject's answers (across the CRT, ICAR, and Raven's tests) was chosen at random, and if correct, \$2 was added to their payment. Last, demographic information was collected. We now outline the sunk cost task in greater detail.

The sunk cost task. Subjects in our primary (sunk cost) group were able to earn a lottery (termed an "asset" in the experimental instructions) by sinking sufficient resources into a task of counting letters (similar to that used by Rosaz and Villeval, 2012). Each subject faced a sequence of five blocks of text. For each block they were asked to count the number of occurrences of two different letters under a time limit of 60 seconds (see Figure 1 for a screenshot). For each letter correctly counted (within a margin of error of one), they got one point. If they got a total of 6 out of 10 points or more, they earned the inferior lottery paying \$10 with a 10% chance, \$0 otherwise. To avoid potential emotional primes from valences of familiar words, randomly-selected Latin words (from the Lorem Ipsum corpus) were used.

Figure 1: Real-effort task



Subjects in the sunk cost group entered letter counts for five blocks of text. A timer showed the amount of time remaining (here, 55 seconds). If subjects did not enter a count, their answer was logged as incorrect. If time expired, the answers present were submitted, and the subject automatically progressed to the next page. All these points were covered in the instructions. The words were uploaded as an image file to prevent "CTRL+F" commands from giving the answer. Only integers were accepted.

Pilots revealed substantial heterogeneity in subjects' ability in the task. With a fixed set of text for all subjects, we expected to lose a lot of data because many would fail to reach a particular score out of 10 (and thus not earn a lottery). To increase efficiency, we implemented subject-specific block paths (unknown to subjects). Specifically, based on their performance on the first text block, subjects were branched into five routes (very hard, hard, medium, or easy; some were branched into a very easy route if they also performed poorly in their second block). Tailoring the task to individual ability levels also has the potential advantage of reducing the variation in the amount of resources subjects sunk into the task. In our experiment, 268 of 305 (88%) scored at least 6/10, made it through to the asset choice, and so can be included in all our analyses.

4 Results

We collected data from 528 subjects over July 22-24, 2019. Average completion time was 27m20s. Subjects received \$4.00 for participating, an average hourly wage of \$8.78 (\$11.21 including incentive payments). Subject demographics are given in Appendix D.

4.1 The sunk cost effect

Table 2 reports the proportion of subjects in the three different treatment groups who chose the dominated lottery. We first report that 23% (95CI= $[18, 28]$%) of the 268 subjects in the sunk cost group who earned the dominated lottery from the real-effort task chose to stick with it, which we interpret as evidence of behavior consistent with the sunk cost effect.[10]

In the endowment group, 7% (95CI= $[4, 11]$%) of the 197 subjects chose the dominated asset. The difference in the proportion of irrational decisions between the sunk cost and endowment groups is significantly different from zero ($d = 0.16$; $p < 0.001$): the sunk cost effect was present and not entirely explained by the endowment effect. In fact, in our data the sunk cost motive appeared to exert a significantly greater influence on decisions than the endowment motive per se, with the latter accounting for approximately only a third of the overall effect.

Last, we point out that none of the 25 subjects who were presented with a straight choice chose the dominated alternative. This suggests it is unlikely an individual would choose that asset due to mathematical deficiency, misunderstanding the text, or some experimental demand effect.

Table 2: Behavior consistent with the sunk cost effect

Condition	Choice			Pr(dominated)
	dominated	dominant	n	
Earned via sunk costs	62	206	268	0.231
Endowment only	14	183	197	0.071
Straight choice	0	25	25	0.000
Difference in proportions				0.160
P-value				<0.001

4.2 Drivers of sunk cost behavior

Section 5 first reports that the average marginal effect (AME) of cognitive reflection levels on the probability of sunk cost behavior is significant (both $p < 0.001$) and negative: a one standard deviation increase corresponds to a decrease in the probability of approximately 0.11-0.12.

[10] A different explanation is that performance, rather than sunk cost, matters. If so, subjects scoring higher would be more likely to stick with the dominated lottery, but we find a negative correlation ($r = -0.16$; $p = 0.009$).

Table 3: Determinants of susceptibility to the sunk cost effect

Average marginal effects	Dependent variable: Behavior			
	(1)	(2)	(3)	(4)
Cognitive reflection	-0.112*** (0.023)	-0.116*** (0.023)		
Fluid intelligence			-0.013 (0.030)	-0.009 (0.028)
Crystallized intelligence			-0.173^{***a} (0.028)	-0.175^{***a} (0.030)
Openness			-0.000 (0.022)	-0.000 (0.022)
Demographics		X		X
Observations	265	265	265	265

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. ^{a} Bonferroni-adjusted $p < 0.001$. Average marginal effects with robust standard errors in parentheses. Estimates from the underlying probit regressions are in Appendix E. Regressors are standardized. Behavior is a binary variable = 1 if the subject displayed behavior consistent with the sunk cost effect. Demographics include sex, age, race, household income, education, and conservatism. Of the 268 subjects in the sunk cost treatment group, 3 chose not to specify their sex, leaving 265 for analysis.

Guided by the tripartite theory of the mind of Stanovich (2012), we now assess the strength of inputs of the reflective mind in explaining sunk cost behavior.[11] We find crystallized intelligence to be significant (both $p < 0.001$), but not fluid intelligence or openness to experience, as reported in specifications (3) and (4) of Section 5.[12] Interpreting the estimated AMEs, a one standard deviation increase in crystallized intelligence decreases the probability of sunk-cost behavior by approximately 17-18 percentage points on average[13].

Interpretation. Previous work (Stanovich, 2012; Stanovich and West, 2008, discussed in Section 2) suggests the key to being able to override a heuristically-primed response is recognizing the need to override it in the first place (while the capacity required to avoid the bias once recognized is relatively slight). As such, stocks of knowledge or experience (crystallized intelligence) and openness of mind are likely to matter more than computational power (fluid intelligence). Our results concerning intelligence measures support this hypothesis in the context of sunk costs. A natural interpretation is that a bigger stock of experience is helpful in enabling individuals to recognize instances of the sunk cost effect and thereby avoid them.

Stanovich and West (2008) also argue conventional measures lack the scope to adequately capture the types of knowledge required for situations that invoke behavioral biases, but our evi-

[11] Auxiliary regressions show both fluid and crystallized intelligence are associated with CRT scores (see Appendix F).

[12] The two intelligence measures are of course correlated ($r = 0.60$; $p < 0.001$) and either measure alone explains significant variation in sunk cost behavior. However, when both are included in regressions, only crystallized intelligence retains explanatory power. See Appendix G for the supporting regressions.

[13] It is plausible the relationship between these cognitive traits and sunk cost behaviour might depend on gender; a sub-sample analysis in Appendix H reveals however that the results are similar for male and female subjects.

dence suggests they do not. Contrary to their hypothesis we do not find a relationship between sunk cost behavior and openness to experience. This could be because that personality trait is not a major driver of this mode of thinking, because it is not a major driver of the sunk cost effect, or something particular to our sample; a question for future research.

4.3 SCE-8: A scale to measure susceptibility to the sunk cost effect

We first analyze the latent factor structure of our 528 subjects' responses to the 18 scenarios to identify any underlying factors causing them to covary. Informed by that analysis we select the scenarios to be included in our scale, which we then relate back to behavior.

Exploratory factor analysis. Various checks support the factorability of the data: multicollinearity between the 18 items is low (mean variance inflation factor: 1.22); Bartlett's sphericity test is significant ($\chi^2(153) = 1160.29$; $p < 0.001$); and the Kaiser-Meyer-Olkin measure of sampling adequacy (0.83) surpasses the advised threshold of 0.6 Kaiser and Rice, 1974. Extracting factors with eigenvalues > 1 (the Kaiser criterion; (Kaiser, 1960)), we find one principal factor that explains 90% of the variance (with an eigenvalue of 2.81). A scree test (Cattell, 1966) also supports a one-factor solution, dropping-off substantially after the first factor. Investigating the fit of that solution, we extract one factor and find that the majority (11 of 18) of scale items load well onto it (with a loading > 0.32; Costello and Osborne, 2005), as reported in the first row of Table 4.

Table 4: Factor loadings by scenario ID

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
25	18	50	28	24	46	35	39	39	57	49	59	20	43	53	44	30	3
-	-	48	-	-	48	-	-	-	56	48	62	-	44	55	50	-	-

Loadings are multiplied by 100. The first and second rows report the loadings from the factor analysis with all 18 and the selected 8 (SCE-8 scale) scenarios, respectively.

We follow recommended practice and drop items with weak loadings (< 0.32). We also drop items that fail to meet this threshold when excluding subjects ($n = 40$) who completed the 18 scenarios in less than 90 seconds (items 7 and 8). Finally, we drop item 9 because its loading of 0.34 (after dropping 7 and 8) is marginal and because time (the predominant resource it relates to) is well represented by several other items with strong loadings. The loadings generated from the remaining 8 scenarios are given in the second row of Table 4. A reliability analysis of those items demonstrates internal consistency (Cronbach's alpha = 0.75).[14]

Confirmatory factor analysis. To confirm the suitability of a one-factor representation of these 8 items, we estimate a structural equation model that links subjects' responses to them with one latent variable. We find the standardized factor loadings of each of the 8 items to be

[14]A scale with all 11 items with initial loadings > 0.32 yields a negligibly higher Cronbach's alpha of 0.749 (cf. 0.747 with 8 items), owing to the fact that the additional three items have notably weaker loadings.

significant ($p < 0.001$) and above the recommended value (0.32). Goodness-of-fit measures are also satisfactory: the standardized root mean squared error is 0.02, falling in the "good" to "excellent" range (0.01-0.05; MacCallum et al., 1996), while the χ^2-to-degrees-of-freedom ratio is 1.02 (ratios between 1-3 are acceptable, with values closer to 1 indicating a better fit; Bollen and Scott Long, 1993). We name the 8-scenario scale the "SCE-8". The scale is provided in Appendix I, and the corresponding scores of our subjects in Appendix J.

Interpretation. Across the scenarios, different types of costs are sunk to different degrees. We interpret the emergence of a single factor as the best representation of the data as reflecting both the idea that the sunk cost effect applies across resources, and the highly interdependent nature of the resources involved. Moreover, amongst the scenarios with the highest loadings, there is at least one scenario in which each of the main resources covered is the predominant resource (see Tables 1 and 4), further suggesting that the factor is relevant for various kinds of sunk cost.

Validating a sunk cost scale with real decisions. Sunk cost behavior and our SCE-8 scale have a significant pairwise correlation ($r = 0.26$; $p < 0.001$). Furthermore, as Table 5 shows, the scale is significantly associated to cognitive reflection (both $p < 0.001$), just as our behavioral measure is (as seen in Section 5). Interpreting the coefficients, a one standard deviation increase in cognitive reflection is associated with an approximate decrease of 0.4 standard deviations in susceptibility to the sunk cost effect as measured by the SCE-8. Moreover, unpacking cognitive reflection into three components, we find that crystallized intelligence is significantly associated with SCE-8, just as our behavioral measure is. These findings and consistencies lead us to conclude that the SCE-8 scale is an appropriate substitute for a behavioral measure.

Table 5: Determinants of the SCE-8

Average marginal effects	Dependent variable: SCE-8			
	(1)	(2)	(3)	(4)
Cognitive reflection	-0.421*** (0.055)	-0.417*** (0.058)		
Fluid intelligence			-0.121 (0.068)	-0.125 (0.068)
Crystallized intelligence			-0.339^{***a} (0.081)	-0.330^{***a} (0.082)
Openness			-0.152* (0.066)	-0.116 (0.070)
Demographics		X		X
Observations	265	265	265	265

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. ^{a} Bonferroni-adjusted $p < 0.01$. OLS regressions. All variables are standardized. Robust standard errors are in parentheses. Specification testing prompted the inclusion of squared and interaction terms of the three trait measures in (3)-(4), and so average marginal effects are reported. Demographics include sex, age, race, household income, education, and conservatism. Of the 268 subjects in the sunk cost treatment group, 3 chose not to specify their sex, leaving 265 for analysis.

5 Discussion

The sunk cost effect is one of the most well-known biases in decision making. Our work advances the identification, understanding, and measurement of the effect.

In contrast to existing research, we provide significant evidence of the sunk cost effect through an incentivized experiment with human subjects. In addition, and to aid our design, we offer a formal choice-based definition. In our sample, we also showed that the endowment effect, far from accounting for all of it, is approximately only a third as strong as the sunk cost effect. This result has implications beyond the detection of these effects: showing that people are more attached to their resources when they are earnt rather than given helps to explain the observation that individuals are less inclined to redistribute when they believe that effort plays more of a role relative to luck in society (Alesina and Angeletos, 2005).

Second, we find strong evidence that capacity for cognitive reflection is negatively related to sunk cost behavior: the ability to override one's instinctive response matters for overcoming the effect. Moreover, our results support the intuitive hypothesis that one's stock of knowledge and experience is predictive of susceptibility to the sunk cost effect, rather than computational ability. This carries an important and subtle point: we find some measures of intelligence to be highly correlated with the sunk cost effect and others not. This could explain the mixed results in the literature and provides a warning: depending upon which measure is used, it is possible to miss the association between the sunk cost effect and cognitive ability.

Third, we offer a scale – the SCE-8 – for researchers to measure susceptibility to the sunk cost effect, without needing to conduct an experiment. The SCE-8 covers a range of costs, capturing the generality of the effect, and appears a good substitute for a behavioral measure. The SCE-8 can be incorporated easily into applied work and can either serve as a measure of interest per se, or as a control just as other measures have been for decades.

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[Susceptibility to the Sunk Cost Effect]

Task 1: Choices in hypothetical scenarios

You will be presented with 18 hypothetical scenarios, each of which lead to a choice. For each one, tell us what you would do.

[Scenario IDs are shown in braces below. Items were presented in a random order.

Responses were recorded via a 6-point Likert scale with the two alternative actions written above the left-most and right-most radio buttons. For each scenario below, those words are provided. In each case, one alternative corresponds to behavior consistent with the sunk cost effect.]

[1.] You are buying a gold ring on layaway for someone special. It costs $200 and you have already put down $100 for it, so you owe another $100. One day, you see in the paper that a new jewelry store is selling the same ring for only $90 as a special sale, and you can pay for it using layaway. The new store is across the street from the old one. If you decide to get the ring from the new store, you will not be able to get your money back from the old store, but you would save $10 overall.
[Continue paying at the old store; Buy from the new store.]

[2.] You enjoy playing tennis, but you really love bowling. You just became a member of a tennis club and a bowling club at the same time. The membership to your tennis club costs $200 per year and the membership to your bowling club $50 per year. During the first week of both memberships, you develop an elbow injury. It is painful to either play tennis or bowl. Your doctor tells you that the pain will continue for about a year.
[Play tennis; Bowl.]

[3.] You have been looking forward to this year's Halloween party. You have the right cape, the right wig, and the right hat. All week, you have been trying to perfect the outfit by cutting out a large number of tiny stars to glue to the cape and the hat, and you still need to glue them on. On the day of Halloween, you decide that the outfit looks better without all these stars you have worked so hard on.
[Wear stars; Go without.]

[4.] After a large meal at a restaurant, you order a big dessert with chocolate and ice cream. After a few bites you find you are full and you would rather not eat any more of it.
[Eat more; stop eating.]

[5.] You are staying in a hotel room, and you have just paid $6.95 to watch a non-refundable movie on pay TV. You then discover that there is a movie you would much rather see on one of the free cable TV channels. You only have time to watch one of the two movies.
[Watch free cable; Watch paid-for movie.]

[6.] You have been asked to give a toast at your friend's wedding. You have worked for hours on this one story about you and your friend taking drivers' education, but you still have some work to do on it. Then you realize that you could finish writing the speech faster if you start over and tell the funnier story about the dance lessons you took together.
[Finish the toast about driving; Rewrite the toast about dancing.]

[7.] You decide to learn to play a musical instrument. After you buy an expensive cello, you find you are no longer interested. Your neighbor is moving and you are excited that she is leaving you her old guitar, for free. You'd like to learn how to play it.
[Practice the cello; Practice the guitar.]

[8.] You and your friend are at a movie theater together. Both of you are getting bored with the storyline. You'd hate to waste the money spent on the ticket, but you both feel that you would have a better time at the coffee shop next door. You could sneak out without other people noticing.
[Finish the movie; Leave for the coffee shop.]

[9.] You and your friend have driven halfway to a resort. You both feel sick and think that you would have a much better weekend at home. Your friend says it is “too bad” you already drove halfway, because you both would much rather spend the time at home. You agree.
[Turn back; Drive on.]

[10.] You are painting your bedroom with a sponge pattern in your favorite color. It takes a long time to do. After you finish two of the four walls, you realize you would have preferred the solid color instead of the sponge pattern. You have enough paint left over to redo the entire room in the solid color. It would take you the same amount of time as finishing the sponge pattern on the two walls you have left.
[Finish the sponge pattern; redo the room in a solid color.]

[11.] You have invested a good deal of your time into a project and it is failing. You have the option to start on something different that you now know is more likely to be successful but you know you cannot get the time back that you spent on the project.
[Keep going with the project; Start something different.]

[12.] You have an investment strategy that you have developed over several months. It is not working and you are losing money, but there is no way for you to recover the lost effort put into developing the strategy.
[Start afresh; Keep going.]

[13.] Imagine that you have spent $20 on a ticket to a concert. The day of the concert comes but unfortunately it is snowing heavily and you feel tired after a tough day. You know you would not have decided to go to the concert if you hadn't already bought the ticket, but you also know that you cannot get a refund.
[Go to the concert; Stay at home.]

[14.] Your relationship with your partner is not going well. You have reasoned it out and you have realized that if you knew how it would go when you started the relationship you would not have gone through with it. You now have the opportunity to break up, but you have been together for many months.
[Keep going; Break up.]

[15.] You have been thinking about how to vote in an election and have invested a good deal of your time to try and make the right decisions including reading newspapers and comment pieces online and thinking hard about the issues. You discover that much of the information you were using is false and a more trustworthy source suggests your initial view was wrong.
[Keep beliefs; change beliefs.]

[16.] You have been thinking hard about the best route to get to somewhere you haven't been to before. Unfortunately, your internet connection isn't working so you have to base your decision on your beliefs about the town's layout. You come to a conclusion on the best possible route but then suddenly the internet is back online.
[Look up route online; Stick to planned route.]

[17.] You are working on a difficult logic problem. Below the problem is a list of possible answers labelled a to e. Although you are not very confident about your answer you decide to go for option a. A friend you know is usually better at this sort of problem suggests that you should change your answer to option b.
[Answer a; Answer b]

[18.] You have been living in a town where it rains a lot and decide to go and buy a high-quality umbrella that you can carry with you every time you go out. Soon after buying a very expensive umbrella you move to a town where it rains much less often.
[Take umbrella with me; Leave umbrella at home.]

Table: Subject Demographics

Characteristic	
Gender	
Male	315 (60)
Female	209 (40)
Other / Prefer not to say	4 (0)
Age, mean years [sd]	34.8 [10.3]
18-25	75 (14)
26-30	151 (29)
31-40	176 (33)
41-50	76 (14)
51+	50 (9)
Race	
White	359 (68)
Black or African American	70 (13)
Hispanic or Latino	40 (8)
American Indian or Alaska Native	4 (1)
Asian American	41 (8)
Native Hawaiian or Pacific Islander	0 (0)
Other	14 (3)
Income[a]	
0 – 9.999	16 (3)
10 – 19.999	48 (9)
20 – 29.999	79 (15)
30 – 39.999	79 (15)
40 – 49.999	71 (13)
50 – 59.999	63 (12)
60 – 69.999	38 (7)
70 – 79.999	32 (6)
80 – 89.999	19 (4)
90 – 99.999	30 (6)
100 – 124.999	24 (5)
125 – 149.999	14 (3)
150+	15 (3)
Education	
High school (grades 9-12, no degree)	5 (1)
High school graduate (or equivalent)	66 (13)
Some college (1-4 years, no degree)	175 (33)
Bachelor's degree (BA, BS, AB, etc)	228 (43)
Master's degree (MA, MS, MENG, MSW, etc)	47 (9)
Professional school degree (MD, DDC, JD, etc)	5 (1)
Doctorate degree (PhD, EdD, etc)	2 (0)
Political Affiliation[b] [sd]	36.6 [31.0]
N	528

Frequencies; (% within characteristic); [standard deviation]
[a] Household annual pre-tax income in '000 USD
[b] 0 = "Entirely Liberal"; 100 = "Entirely Conservative"

Table: Probit coefficients underlying the average marginal effects of Section 5

	Dependent variable: Behavior			
	(1)	(2)	(3)	(4)
Cognitive reflection	-0.399***	-0.430***		
	(0.091)	(0.093)		
Fluid intelligence			-0.052	-0.038
			(0.120)	(0.117)
Crystallized intelligence			-0.696***	-0.728***
			(0.131)	(0.141)
Openness			-0.002	0.002
			(0.088)	(0.092)
Female		-0.288		-0.210
		(0.190)		(0.200)
White		-0.317		-0.139
		(0.199)		(0.220)
Age		0.035		0.051
		(0.055)		(0.057)
Age^2		-0.000		-0.001
		(0.001)		(0.001)
College		0.278		0.289
		(0.198)		(0.201)
Income		-0.007		-0.000
		(0.024)		(0.028)
Conservatism		-0.000		-0.002
		(0.003)		(0.003)
Constant		-1.283		-1.818
		(1.047)		(1.084)
Observations	265	265	265	265

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Probit regressions. Regressors are standardized. Behavior is a binary variable = 1 if the subject displayed behavior consistent with the sunk cost effect. Estimated coefficients shown with robust standard errors in parentheses. Of the 268 subjects in the sunk cost treatment group, 3 chose not to specify their sex, leaving 265 for analysis.

Table: Inputs of the reflective mind

Average marginal effects	Dependent variable: Cognitive reflection	
Fluid intelligence	0.196^{***a}	0.193^{***a}
	(0.044)	(0.045)
Crystallized intelligence	0.539^{***a}	0.527^{***a}
	(0.036)	(0.037)
Openness	-0.020	-0.006
	(0.029)	(0.030)
Demographics		X
Observations	524	524

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. ^{a} Bonferroni-adjusted $p < 0.001$. OLS regressions. Robust standard errors in parentheses. Regressors are standardized. Specification testing prompted the inclusion of squared, cubed, and interaction terms of the three trait measures, and so average marginal effects are reported. Demographics include sex, age, race, household income, education, and conservatism. Of the total 528 subjects, 4 chose not to specify their sex, leaving 524 for analysis.

Table: Supporting results to Section 5

AMEs	Dependent variable: Behavior							
Fluid int.	-0.112***	-0.107***					-0.013	-0.009
	(0.025)	(0.025)					(0.030)	(0.028)
Cryst. int.			-0.181***	-0.181***			-0.173^{***a}	-0.175^{***a}
			(0.023)	(0.026)			(0.028)	(0.030)
Openness					-0.033	-0.024		
					(0.026)	(0.026)		
Demos.		X		X		X		X
Obs.	265	265	265	265	265	265	265	265

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. ^{a} Bonferroni-adjusted $p < 0.001$. Probit regressions. Average marginal effects with robust standard errors in parentheses. Regressors are standardized. Behavior is a binary variable = 1 if behavior was consistent with the sunk cost effect. Demographics include sex, age, race, household income, education, and conservatism. Of the 268 subjects in the sunk cost treatment group, 3 chose not to specify their sex, leaving 265 for analysis.

Table: Determinants of susceptibility to the sunk cost effect (Male Subjects)

Average marginal effects	Dependent variable: Behavior			
	(1)	(2)	(3)	(4)
Cognitive reflection	-0.114***	-0.101***		
	(0.0305)	(0.0316)		
Fluid intelligence			-0.010	-0.008
			(0.037)	(0.036)
Crystallized intelligence			-0.160***	-0.157***
			(0.033)	(0.037)
Openness			-0.023	-0.026
			(0.028)	(0.028)
Demographics		X		X
Observations	155	155	155	155

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Average marginal effects with robust standard errors in parentheses. Regressors are standardized. Behavior is a binary variable = 1 if the subject displayed behavior consistent with the sunk cost effect. Demographics include age, race, household income, education, and conservatism.

Table: Determinants of susceptibility to the sunk cost effect (Female Subjects)

Average marginal effects	Dependent variable: Behavior			
	(1)	(2)	(3)	(4)
Cognitive reflection	-0.125***	-0.135***		
	(0.036)	(0.036)		
Fluid intelligence			-0.004	0.003
			(0.045)	(0.041)
Crystallized intelligence			-0.226***	-0.216***
			(0.051)	(0.051)
Openness			0.064	0.053
			(0.041)	(0.041)
Demographics		X		X
Observations	110	110	110	110

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$. Average marginal effects with robust standard errors in parentheses. Regressors are standardized. Behavior is a binary variable = 1 if the subject displayed behavior consistent with the sunk cost effect. Demographics include age, race, household income, education, and conservatism.

SCE-8: A scale to measure susceptibility to the sunk cost effect

You will be presented with 8 hypothetical scenarios, each of which lead to a choice. For each one, tell us what you would do. For each item subjects have a 6-point scale for which the two alternatives are written over the left-most and right-most points. The alternatives are provided after each scenario below.]

A. You have been looking forward to this year's Halloween party. You have the right cape, the right wig, and the right hat. All week, you have been trying to perfect the outfit by cutting out a large number of tiny stars to glue to the cape and the hat, and you still need to glue them on. On the day of Halloween, you decide that the outfit looks better without all these stars you have worked so hard on. [Wear stars; Go without.]

B. You have been asked to give a toast at your friend's wedding. You have worked for hours on this one story about you and your friend taking drivers' education, but you still have some work to do on it. Then you realize that you could finish writing the speech faster if you start over and tell the funnier story about the dance lessons you took together. [Finish the toast about driving; Rewrite the toast about dancing.]

C. You are painting your bedroom with a sponge pattern in your favorite color. It takes a long time to do. After you finish two of the four walls, you realize you would have preferred the solid color instead of the sponge pattern. You have enough paint left over to redo the entire room in the solid color. It would take you the same amount of time as finishing the sponge pattern on the two walls you have left. [Finish the sponge pattern; Redo the room in a solid color.]

D. You have invested a good deal of your time into a project and it is failing. You have the option to start on something different that you now know is more likely to be successful but you know you cannot get the time back that you spent on the project. [Keep going with the project; Start something different.]

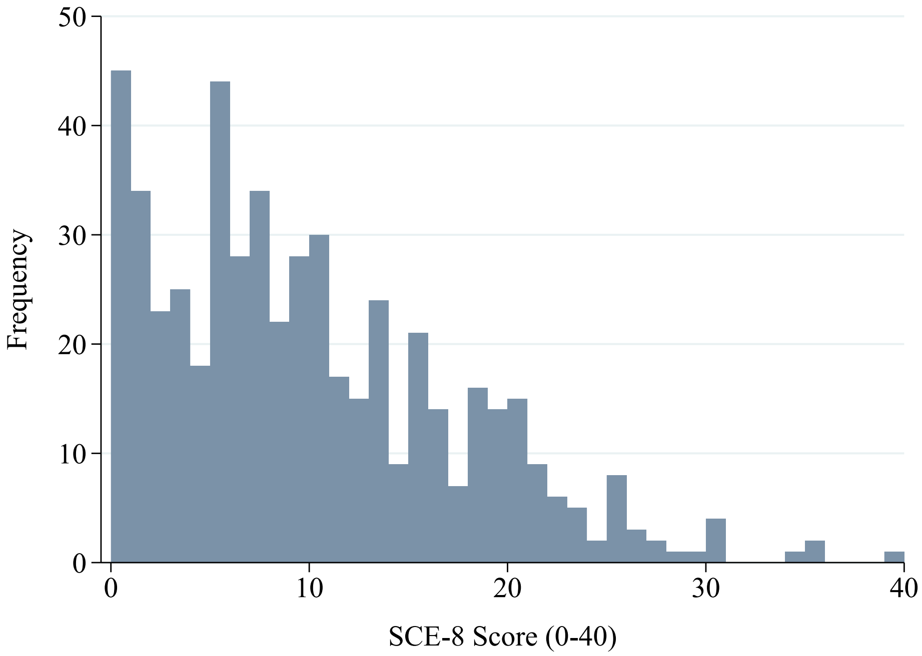
E. You have an investment strategy that you have developed over several months. It is not working and you are losing money, but there is no way for you to recover the lost effort put into developing the strategy. [Start afresh; Keep going.]

F. Your relationship with your partner is not going well. You have reasoned it out and you have realized that if you knew how it would go when you started the relationship you would not have gone through with it. You now have the opportunity to break up, but you have been together for many months. [Keep going; Break up.]

G. You have been thinking about how to vote in an election and have invested a good deal of your time to try and make the right decisions including reading newspapers and comment pieces online and thinking hard about the issues. You discover that much of the information you were using is false and a more trustworthy source suggests your initial view was wrong. [Keep beliefs; Change beliefs.]

H. You have been thinking hard about the best route to get to somewhere you haven't been to before. Unfortunately, your internet connection isn't working so you have to base your decision on your beliefs about the town's layout. You come to a conclusion on the best possible route but then suddenly the internet is back online. [Look up route online; Stick to planned route.]

Figure: SCE-8



Subjects' scores (n = 528) on the SCE-8 scale. Each scenario is responded to on a 6-point Likert scale and is coded 0-5 such that the higher the score, the higher the susceptibility, hence the range is 0-40. Summary statistics for our sample: min 0, max 40, average 9.5, median 8, inter-quartile range [4,15], and standard deviation 7.5.

Mindfulness & Information Acquisition*

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Abstract

Mindfulness meditation has been found to influence various economically-relevant outcomes such as health, stress, depression, productivity and altruism. We report evidence from a randomised-controlled trial on a previously-untested effect of mindfulness: information avoidance. We find that a relatively short mindfulness treatment (two weeks, 15 minutes a day) is able to induce a statistically significant reduction in information avoidance in comparison to the control. Supplementary evidence supports mindfulness's effects on emotion regulation as a possible mechanism for the effect. Viewing mindfulness as both a skill and a trait, our study has significant implications for both policy and the wider population. *JEL: D91, I31, C91*

Keywords: mindfulness, information avoidance, randomized controlled trial.

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¶***My Contribution:*** Tuckwell was the lead investigator of this paper.

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1 Introduction

A well-known bias in individual decision-making is the tendency to avoid information about potentially negative outcomes, even if it is freely available. Information avoidance can be costly: an individual's ability to make good decisions hinges critically on their knowledge of the state of the world. Previous work suggests that anticipatory emotions (such as worry or regret) play an important role in information avoidance[1]. It is therefore plausible that mental training that targets the regulation of such emotions might help to diminish their influence in decision making. One such form of mental training is "mindfulness" meditation: a secularised form of Buddhist meditation, initially developed for pain management (Kabat-Zinn, 1990). It has become increasingly popular in the West in recent decades, and has been linked with various beneficial effects, e.g. for health, stress, depression and productivity (Brown et al., 2007). The meditation encourages a particular state of mind (non-judgmental attention to the present moment) and various evidence from psychology and neuroscience has demonstrated that its practice can increase levels of attention and emotion regulation (and, indeed, structurally change regions of the brain associated with such tasks[2]). However, mindfulness can be viewed as a trait as well as a meditation practice (Brown and Ryan, 2003): different individuals naturally spend more or less time in such mindful states even if they have never meditated, so its study has implications for non-meditators as well. Reporting evidence from a Randomised-Controlled Trial (RCT), this paper will examine whether mindfulness can influence information avoidance.

We designed a trial[3] ($n = 261$) where subjects were randomly allocated to either a treatment intervention (14 days of 15-minute guided mindfulness meditations), or an active control intervention (14 days of 15-minute guided relaxing-music listening[4]) which allowed us to test the effects of mindfulness over-and-above just feeling more relaxed. Utilising a recently-developed information avoidance scale (Ho et al., 2020), we found that the effect of the mindfulness treatment was to reduce information avoidance (by approximately 0.25 standard deviations) relative to the control. Additional evidence supports emotion regulation as a plausible mechanism, with the treatment having a positive effect on a self-report measure of non-reactivity to inner experience.

We next review the relevant literature and our relative contribution, before detailing the design and results. We end with a discussion and some concluding remarks.

2 Literature

Our work firstly relates to the literature on the causes of information avoidance. This literature has documented various potential causes, with Golman et al. (2017) grouping them into hedonic

[1]See Golman et al. (2017) for a review.

[2]See Hölzel et al. (2011) for a review.

[3]Pre-registered in the AEA RCT Registry (Ash et al., 2020).

[4]The same instructor delivered both the treatment and the active control.

(avoiding information to avoid feeling bad, e.g. because of belief-based utility) and strategic (as a way to committing to an a priori preferred course of action). However, relatively little is understood about the psychological and cognitive forces that make different individuals more or less susceptible to avoiding information. In part this could be because of a lack of a measure of information avoidance as a psychological construct, which was the motivation for Ho et al. (2020) to produce the scale we use in this paper. Sweeny et al. (2010) mention some empirical work that suggests coping styles and uncertainty orientation as two possible explanations for individual differences in information avoidance; our paper adds to this literature by documenting the role of mindfulness (which can be viewed as a trait).

We expect mindfulness to act on the hedonic form of information avoidance, where individuals avoid information about their beliefs because of psychological costs such as worry, regret, disappointment, pessimism or cognitive dissonance (Golman et al., 2017). Because the mindful state of mind encourages individuals to not be wrapped up in thoughts and beliefs as if they were strictly true (the quality of "non-judgment"), and instead hold them lightly in awareness (a concept known as "meta-awareness")[5], it is possible mindfulness weakens the potential emotional imprint of beliefs, reducing the influence of worry, regret etc. In support of this, Saunders et al. (2013) find that mindfulness increases recall of self-threatening information. And, more indirectly, mindfulness has been shown to reduce symptoms of belief-based utility, such as anxiety (Roemer et al., 2009) and habitual worrying (Verplanken and Fisher, 2014). In general, mindfulness has been found to increase abilities to regulate emotions; for example, reducing emotional interference when performing a task (Ortner et al., 2007) and decreasing emotional reactivity (Goleman and Schwartz, 1976). Researchers point to people in mindful states being better able to "reappraise" emotions (Garland et al., 2011) which means they are more equipped to process uncomfortable emotions, and less likely to engage in experiential avoidance of thoughts, feelings etc. (Kumar et al., 2008). Supporting this work is neuroscientific evidence that shows that meditators have increased activation in regions of the brain associated with emotion regulation (Hölzel et al., 2011).

Our paper also relates to a literature that investigates the influence of mindfulness on economic decision-making. Alem et al. (2016) conduct an RCT which tested whether mindfulness influenced risk, time preferences and health-related behaviours (e.g. smoking, eating, alcohol consumption, sleeping), but their results in general were not statistically significant. Moreover, their active control (watching a historical documentary) does not specifically control for being relaxed, so it is hard to disentangle the effects of being mindful from being relaxed in their results (they could go in opposite directions). Noone and Hogan (2018) conduct an RCT to investigate the effects of mindfulness on various cognitive tasks (that included a heuristics-and-biases measure). They used the Headspace app to deliver either a mindfulness intervention or a sham meditation active control and did not find statistically significant effects. The authors

[5] See Schooler et al. (2011) for a review.

cannot conclude whether the lack of significance was because of the short treatment not being effective enough, or whether the sham meditation might have engendered small amounts of mindfulness (perhaps through an expectation effect). Our study finds instead that it is possible to influence cognitive biases with only small amounts of mindfulness training. Other papers contain stronger evidence of mindfulness's effects on economic decision-making, finding that mindfulness can make decisions more adaptive (in a gambling context) (Lakey et al., 2007); reduce negativity bias (Kiken and Shook, 2011); reduce the corespondence bias (Hopthrow et al., 2017); decrease the sunk cost effect (Hafenbrack et al., 2014); improve addiction and self-control problems[6]; and increase levels of altruism (Iwamoto et al., 2020). Our paper adds information avoidance to these documented effects.

3 Experimental Design

3.1 Sample

We recruited 261[7] subjects in one wave for the experiment using Prolific, an online crowdsourcing platform (based in the UK) which connects researchers to participants for academic studies. A more commonly used crowdsourcing platform is MTurk. Like MTurk, Prolific has been found to produce data of a comparable quality to more traditional participant pools (Peer et al., 2017) and been used to successfully run experiments in economics (e.g. Marreiros et al., 2017) and psychology (e.g. Callan et al., 2017). However, Prolific has the advantage of participants who are more naive with respect to experimental tasks and less dishonest than those on MTurk (Peer et al., 2017). We also wanted to restrict participation to those in the UK (to maximise comprehension and familiarity with the instructor's English accent) and Prolific has a more active presence there than MTurk. The subjects we recruited were invited to take part in a study that investigated the effects of mood on decision-making, which involved doing a simple and enjoyable activity for 15 minutes a day on 14 consecutive days. Each day, the instructions for the activity were to be given by a professional instructor via an audio recording. On the day before and day after the course, the subjects took a survey (which measured our outcomes). The subjects were paid for doing the activity (£2 per session in the first week; £2.50 per session in the second week) and taking the surveys (£2 for the pre-course survey; £3 for the post-course survey). Moreover, to minimise attrition, subjects were told on sign-up that their submissions would only be "accepted" (i.e. they would only be paid) if they completed all parts of the study (unless there were exceptional circumstances). Various compliance measures are discussed below.

The software o-Tree was used to host the surveys, while Qualtrics was used to deliver the interventions. We restricted participation to those in the UK, with a good track record (at least 95%

[6]See Zgierska et al. (2009) for a review

[7]Calculations suggested a sample of 220-260 subjects would be adequate to detect effects with 80% power and 5% significance (Ash et al., 2020).

of Prolific studies approved), and some previous experience on the platform (completed at least 10 previous studies). We also prescreened on meditation experience, recruting only participants who had answered "No" to Prolific's own prescreening question, "Do you meditate?".

3.2 Inteventions

After the pre-course survey, subjects were randomly allocated to one of two groups: a *mindfulness* intervention (the treatment), and a *music* intervention (an active control).

Mindfulness intervention. Here the instructor led the participants in a guided mindfulness meditation each day. Each session started with a short introduction (welcoming the participants). The instructor then led the participants through three stages of meditation: (1) bringing awareness to now (noticing what is happening outside and how you are); (2) mindful breathing (being aware of the breath and cultivating an attitude of non-judgment as thoughts arise); and (3) a body scan (expanding this awareness from the breath to the entire body). This was then followed by an unled period where the participants were asked to just sit with whatever awareness they had accumulated, before the instructor came back to end the session.

Music intervention. Here the same instructor led the participants in a period of relaxing music listening each day. The idea of the intervention was to try to control for as many of the structural elements of the treatment as possible (15 minutes a day of doing an activity instructed by an audio recording, with the same instructor leading the activity), and in addition control for the relaxing effects of the meditations[8]. To try to make the instructor's presence felt as much as in the treatment, the instructor spent time on a short introduction before the music began (welcoming the participants, mentioning the details of the artist/album etc., and also reciting a famous quote about music for the participants to contemplate), and after the music finished he would come back to end the session like in the other group.

In order to boost feelings of instructor-participant interaction for both groups (and help minimise attrition), the instructor prepared three short videos of himself to be played at the start, middle and end of the interventions (simple check-ins). In addition, participants were sent daily reminders on Prolific about the activity sessions. Compliance was encouraged before the recordings began with a request to close all sources of distraction and to stay on the browser tab (and not multitask). Compliance was then monitored by different measures: (1) how often they left their browser tab during the recording; (2) whether they clicked to the "next page" when the instructor asked them to at the end of the recording. We also included an optional feedback question about their experience of the session at the end.

[8]Various studies document the salutary effects of music for stress (see de Witte et al. (2020) for an overview.). In some contexts music has been found to have comparable effects to meditation in reducing stress (e.g. Innes et al., 2016), and has previously been used as part of an active control for the widely-used Mindfulness-Based Stress Reduction (MBSR) programme (MacCoon et al., 2012). Stress impacts cognitive processes (e.g. "System 1" and "System 2" thinking (Kahneman, 2011)) that underlie various kinds of decisions (including information avoidance) so is important to control for if possible.

3.3 Procedure

The study was launched on Thursday the 27th of August, 2020. On the first day we recruited 261 subjects, who signed up and completed the pre-course survey. Then from the 28th of August through to the 11th of September, each day the subjects were invited to complete a session of the daily activity (study available from 6am; reminder sent at 3pm), and were asked to submit by 3am the following day. Participants who missed a session were asked to do the session on the following day instead. Participants who attempted a session but had difficulties finishing it for some reason (e.g. because of internet trouble, etc.) were allowed to miss the session. Any participant who missed more than one session without giving a reason was excluded. On the 12th of September, they were invited to do the post-course survey.

3.4 Outcomes

Information avoidance. We used the *Information Preference Scale* (IPS) (Ho et al., 2020): a 13-item scale (validated by an incentivised experiment) that measures an individual's willingness to receive information that might cause worry or regret in a series of thirteen hypothetical scenarios[9]. Items are responded to on a 4-point scale coded $\{0, \ldots, 3\}$, giving scores $\{0, \ldots, 39\}$. Due to the transparent nature of the questions, information preferences were measured in the post-course survey only.

Mindfulness. We used the 15-item version of the *Five Facet Mindfulness Questionnaire* (FFMQ) (Baer et al., 2012), a frequently-used measure of mindfulness and its underlying dimensions (Sauer et al., 2013). Items are responded to on a 5-point scale coded $\{0, \ldots, 4\}$, giving a mindfulness score of $\{0, \ldots, 60\}$, but the scale can also be disaggregated into subscales that measure five attributes of mindfulness: observing, describing, acting with awareness, non-judging of inner experience and non-reactivity to inner experience (3 items in each, scores $\{0, \ldots, 12\}$). Due to its transparency, this outcome was also measured in the post-course survey only.

Stress. We used the 10-item version of the *Perceived Stress Scale* (PSS) (Cohen and Williamson, 1988), a widely-used instrument to assess subjective perceptions of stress (Liu et al., 2020). Items are responded to on a 5-point scale coded $\{0, \ldots, 4\}$, giving scores $\{0, \ldots, 40\}$.

3.5 Empirical Strategy

To measure the effect of the treatment on information avoidance (measured in the post-course survey only) we ran the following OLS regression:

$$Y_i = \alpha + \beta \text{Treat}_i + \gamma X_i + \epsilon_i \tag{1}$$

Where Y_i is the outcome, Treat_i is a dummy variable equal to 1 for individuals in the mindfulness treatment, and X_i is a vector of individual characteristics measured at baseline.

[9]See Appendix A-C for the items of the IPS, FFMQ and PSS measures.

4 Results

4.1 Baseline Characteristics

Table 1 shows the sample characteristics for a set of baseline measures. The randomisation appears to be well balanced, with no significant differences in the means of these observable characteristics between the treatment and control groups prior to the interventions.

Table 1: Baseline Characteristics

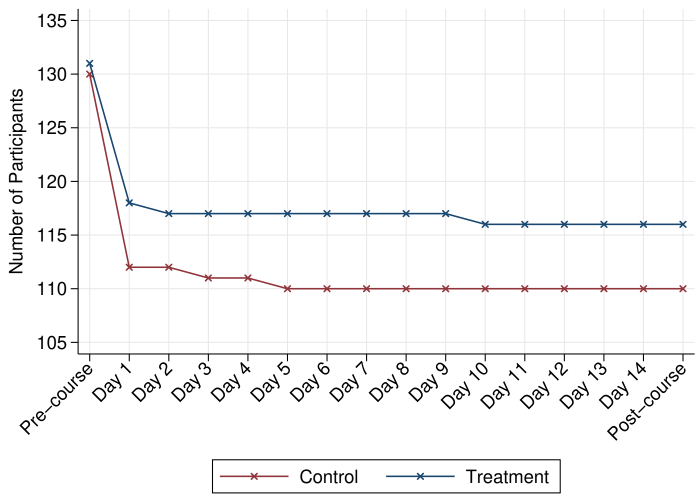
Variables	**All**		**Treatment**		**Control**		**Diff**
	Mean	SD	Mean	SD	Mean	SD	Mean
Age[a]	43.81	12.61	43.81	11.73	43.81	13.47	0.00
Female	0.61	0.49	0.60	0.49	0.61	0.49	0.00
White	0.93	0.25	0.92	0.27	0.94	0.24	-0.01
Degree	0.57	0.50	0.55	0.50	0.60	0.49	-0.05
Household income *(1-10)*	4.63	2.30	4.77	2.31	4.49	2.29	0.28
Conservatism *(0-100)*	44.17	22.07	45.57	22.52	42.75	21.60	2.82
Perceived stress *(0-40)*	17.84	3.99	17.78	4.05	17.90	3.94	-0.12
Observations	261		131		130		

Notes: None of the differences in mean were significant at the 10% level. "Degree" is whether they have a Bachelor's degree. "Household income" bracket *i* is (*i*-1)*£10,000 to *i**£10,000 (pre-tax). "Conservatism" is liberal-conservative scale. [a]Two participants in the treatment group did not give their age, so the number of observations on age in the full sample / treatment was 259 / 129.

4.2 Attrition

Levels of attrition were 13% in the treatment and 18% in the control, and mostly occurred after the pre-course survey (see Figure 1).

Figure 1: Number of Participants at Each Session



In Table 2 we check whether the treatment and control groups are still comparable in the sample of non-attritors. Examining the baseline characteristics, we find no evidence for asymmetric attrition, with no significant differences in the means of the treatment and control.

Table 2: Comparison of Baseline Characteristics of Non-Attritors in Treatment and Control

	Difference in Mean
Age	0.118 (1.690)
Female	-0.041 (0.046)
White	-0.013 (0.026)
Degree	-0.093 (0.046)
Household income *(1-10)*	0.337 (0.219)
Conservatism *(0-100)*	2.956 (2.086)
Perceived stress *(0-40)*	0.131 (0.376)

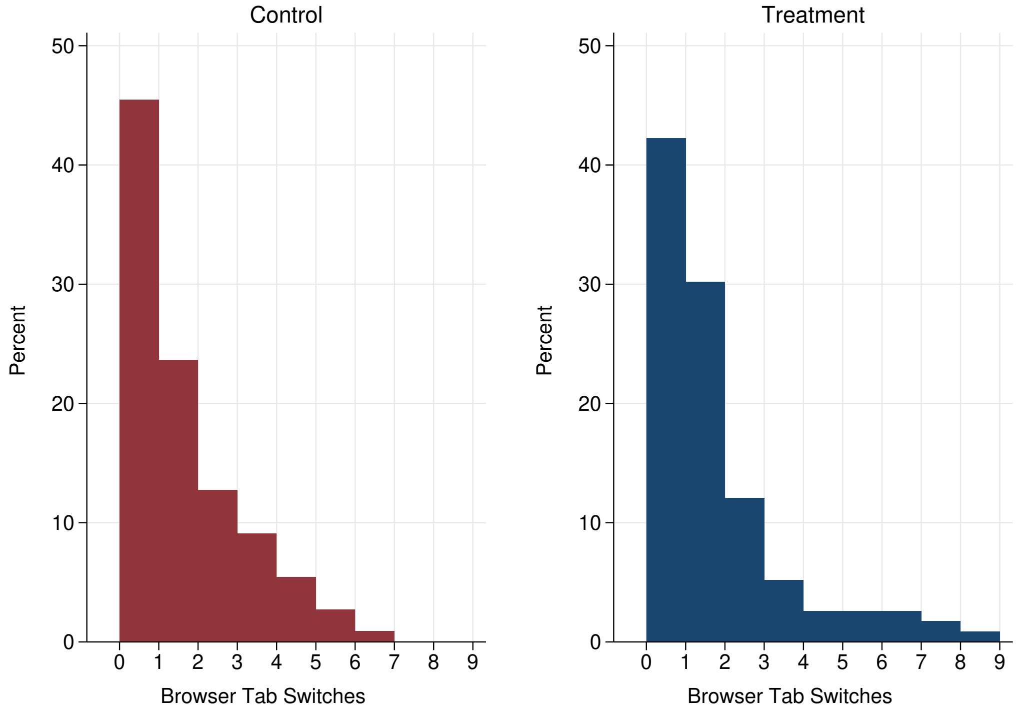
Notes: Standard errors in parentheses. No differences were significant at the 10% level.

4.3 Compliance and Feedback

Participant feedback during the treatment and control interventions was generally positive. After each session participants were asked, "Are you happy with how today's session went?", responding on a 5-point scale: not at all (1); a little (2); moderately (3); very much (4); extremely (5). The average feedback per session was 3.92 in the control and 3.75 in the treatment (see Appendix D for the distributions).

We now evaluate levels of compliance. Our first measure is how often participants switched away from the browser tab with the recording during the interventions. Figure 2 plots the distribution over participants of their average switches per session. The treatment and control groups are fairly similar, with significant proportions focusing during the recordings (over 40% have an average number of switches between 0 and 1). The difference in the mean of the control (1.61) and the treatment (1.72) is not statistically significant (t = 0.680; p = 0.497).

Figure 2: Average Browser Tab Switches per Session

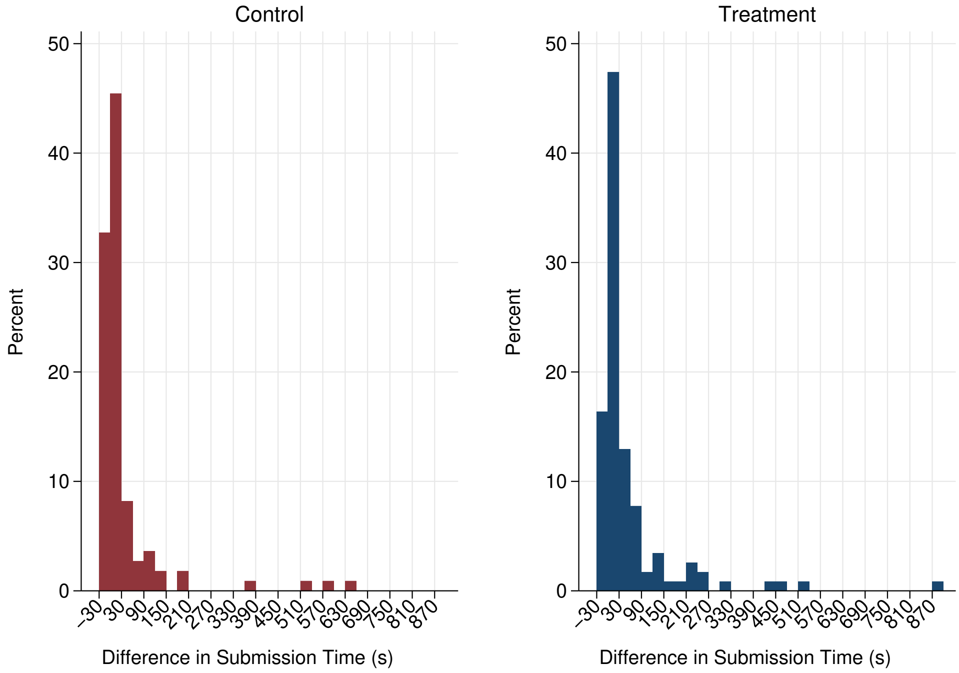


Notes: This figure shows the distributions over participants of the average number of browser tab switches per session during the interventions. The bins are of width 1.

We also measured compliance by seeing whether they clicked to the "next page" when the instructor asked them to at the end of the recording (which gauges if they had been listening). In Figure 3 we show the distribution over participants of the average difference between their submission times and the end of the recording per session. Again the treatment and control group distributions look similar, with a substantial proportion of participants (over 40%) seeming to submit more or less when they are told (within 30 seconds of the end of the recording). The interval with the second-highest density for both groups is between 0 and minus 30 seconds: the next button appears 30 seconds before the end so this could reflect participants clicking as soon as possible for some sessions; however, it is also true the instructor tended to wrap up the sessions in a similar way across the recordings so participants could just be skipping his final remarks because they are used to them. The difference in the mean of the treatment (58 seconds) and control (36 seconds) is again not statistically significant[10] (t = 1.464; p = 0.145).

[10]The means of the treatment and control are significantly influenced by outliers: removing the largest 4 observations decreases the mean of the treatment to 39.7 seconds and the mean of the control to 17.3 seconds.

Figure 3: Average Difference in Submission Time per Session

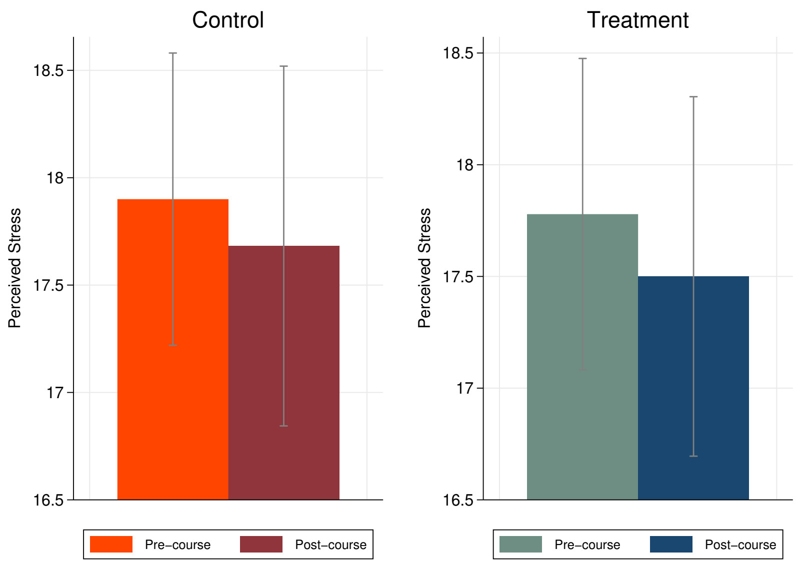


Notes: This figure shows the distributions over participants of their average difference in submission time per session (from the true end of the recording). The bins have a width of 30 seconds.

4.4 Levels of Stress and Mindfulness

Both interventions reduce the point estimates of perceived stress, although the effects are not significant (see Figure 4).

Figure 4: Intervention Effects on Perceived Stress

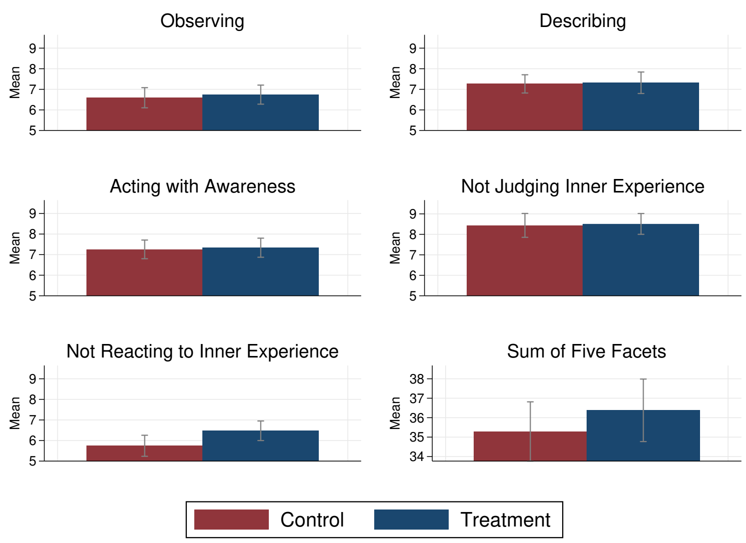


Notes: This figure shows the pre-course and post-course means of perceived stress in the treatment and control. Gray bars show 95% confidence intervals.

It is unclear why the treatment and active control did not have significant effects on reducing stress. It could be that the length of the interventions and amount of practice per day were insufficient to generate significant reductions, or perhaps the perceived stress scale was too noisy a measure to have detected a change with the current sample. In any case, the active control has fulfilled its primary purpose: to provide the equivalent effect on stress as the treatment.

We also collected data on mindfulness using the FFMQ scale. In Figure 5 we can see that the mean of the non-reacting subscale is significantly higher in the treatment than in the control ($t = 2.059$; $p = 0.04$). For the other facets and overall FFMQ the treatment raises the point estimates of the means slightly compared to the control, but the effects are not significant. The evidence suggests that the skill of non-reacting developed strongly as a result of the programme of meditations designed by the instructor.

Figure 5: Intervention Effects on the Five Facets of Mindfulness Scale



Notes: This figure compares the post-course means of the FFMQ scale and sub-scales. Gray bars show 95% confidence intervals.

4.5 Mindfulness and Information Acquisition

We now evaluate the effect of the treatment on information avoidance. As seen in Table 3, being assigned to the treatment has a significant positive effect on preferences to receive potentially negative information as measured by the IPS. Interpreting the coefficients, being in the treatment is associated with an increase of approximately 0.25 standard deviations in information preferences.

Table 3: Effect of the Treatment on Information Preferences

Marginal effects	Information Preference Scale	
	(1)	(2)
Treatment	0.251^{*}	0.230^{*}
	(1.892)	(1.735)
Demographics	No	Yes
Observations	226	224

$^{*}p < 0.10$. Marginal effects from OLS regressions with robust standard errors in parentheses. IPS is standardised. Demographics include sex, age, race, education, household income and conservatism.

4.5.1 Emotion Regulation as a Potential Mechanism

As noted previously, participants in the treatment group scored significantly lower on the non-react scale of the FFMQ in the post-course survey. Figure 6 shows the three items from that scale.

Figure 6: Non-React Scale Items from the FFMQ

"When I have distressing thoughts or images, I "step back" and am aware of the thought or image without getting taken over by it."

"When I have distressing thoughts or images I am able just to notice them without reacting."

"When I have distressing thoughts or images I just notice them and let them go."

The items suggest that the mindfulness training in the treatment cultivated a potential to not react to distressing inner experience. This inner experience could include anticipatory emotions such as worry or regret, so regulation of anticipatory emotions seems like a viable mechanism by which the mindfulness training was able to reduce tendencies for information avoidance. In Table 4 we show that the treatment had a significant effect on the non-react scale when incorporating demographic controls and robust standard errors. Interpreting the coefficients, being in the treatment group is associated with an increase of approximately 0.27 standard deviations in the non-react scale.

Table 4: Effect of the Treatment on Non-Reacting

Marginal effects	Non-React Scale	
	(1)	(2)
Treatment	0.272** (2.057)	0.269** (1.984)
Demographics	No	Yes
Observations	226	224

** $p < 0.05$. Marginal effects from OLS regressions with robust standard errors in parentheses. Non-React Scale is standardised. Demographics include sex, age, race, education, household income and conservatism.

5 Discussion

In this paper we have provided evidence on mindfulness as a cause of differences between individuals in their susceptibility to information avoidance. The costs of information avoidance for individuals, companies and society at large are potentially substantial (from individuals unwilling to learn about their health (including whether or not they carry infectious diseases), to investors holding off looking at their stocks' performance (Ho et al., 2020)) so understanding what might drive some individuals to avoid information more than others is important. Our evidence suggests that people in the population who spend more of their time inhabiting mindful states are better able to look at potentially negative, but nonetheless useful, information about themselves and the world. Supplementary evidence suggests at mindfulness's effects on emotion regulation (specifically, non-reaction to emotions) as a potential mechanism through which this greater tolerance for information operates.

An important concern about the trial is whether subjects in the treatment group actually engaged with the guided meditations. The compliance measures were encouraging in this regard in that it appeared that significant proportions of the subjects were listening to the recordings (e.g. not switching off the browser tab, and clicking to the next page when the instructor asked them to at the end of the recording). However, it could be that the subjects listened to the recordings but did not practice the meditations. Although this is hard to rule out, it seems difficult to square with the evidence, which showed that subjects in the treatment group developed higher levels of non-reaction, a known effect of meditation. An additional concern is that subjects in the treatment group, once they knew that meditation was their daily activity, would have certain expectations about the effects of meditation, and this would then influence their responses on the information avoidance measure (an "experimenter demand" effect). Given that information avoidance is an unknown effect of meditation (not discussed in the public domain), and that no relevant cues were given during the interventions in relation to information avoidance, we are less concerned about experimenter demand in relation to this outcome. Nonetheless, we controlled the expectations that could be managed in the design as best as possible, with both the treatment and control groups being told the same message in regards to their activity at the start of the interventions: that it had been found to have a "positive effect on people's mood and wellbeing".

Our paper therefore adds information avoidance to the growing list of found benefits of mindfulness. This result potentially has strong policy implications. "Nudging" (Thaler and Sunstein, 2009) has become a staple of behavioural policy, being employed in various governments throughout the world. However, by shaping individual choices without their knowledge, it has been criticised as a potential threat to individual autonomy[11]. Making better decisions through greater levels of mindfulness, on the other hand, is a fully conscious process, so mindfulness training could provide governments with a more ethical approach to ameliorating cognitive biases. Our evidence shows that mindfulness is able to reduce information avoidance, but more work is needed to test its effects on a wider array of cognitive biases; for example, mindfulness (by managing the emotions triggered by beliefs) might also affect the processes underlying "motivated beliefs (such as wishful thinking)[12]. We hope our investigation will encourage more research in this area.

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[12]See Bénabou and Tirole (2016) for a review.

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— APPENDIX A —

Information Preference Scale

In each scenario below, you will have an opportunity to receive information. This information may or may not be useful and it may or may not be painful to learn. Please read each scenario carefully, then indicate if you want to know that information. [Choices: Definitely don't want to know; Probably don't want to know; Probably want to know; Definitely want to know. "R" is scored in reverse.]

1) As part of a semiannual medical checkup, your doctor asks you a series of questions. The answers to these questions can be used to estimate your life expectancy (the age you are predicted to live to). Do you want to know how long you can expect to live?

2) You provide some genetic material to a testing service to learn more about your ancestors. You are then told that the same test can, at no additional cost, tell you whether you have an elevated risk of developing Alzheimer's. Do you want to know whether you have a high risk of developing Alzheimer's?

3) At your annual checkup, you are given the option to see the results of a diagnostic test, which can identify, among other things, the extent to which your body has suffered long-term effects from stress. Do you want to know how much lasting damage your body has suffered from stress?

4) Ten years ago, you had the opportunity to invest in two retirement funds: Fund A and Fund B. For the past 10 years, you have invested all your retirement savings in Fund A. Do you want to know the balance you would have if you had invested in Fund B instead?

5) You decide to go to the theater for your birthday and give your close friend (or partner) your credit card so they can purchase tickets for the two of you, which they do. You aren't sure but suspect that the tickets may have been expensive. Do you want to know how much the tickets cost?

6) You bought an electronic appliance at a store at what seemed like a reasonable,though not particularly low, price. A month has passed, and the item is no longer returnable. You see the same appliance displayed in another store with a sign announcing "SALE." Do you want to know the price you could have bought it for?

7) You gave a close friend one of your favorite books for her birthday. Visiting her apartment a couple of months later, you notice the book on her shelf. She never said anything about it; do you want to know if she liked the book?

8) Someone has described you as quirky, which could be interpreted in a positive or negative sense. Do you want to know which interpretation he intended?

9) You gave a toast at your best friend's wedding. Your friend says you did a good job, but you arnt sure if he or she meant it. Later, you overhear people discussing the toasts. Do you want to know what people really thought of your toast?

10) As part of a fundraising event, you agree to post a picture of yourself and have people guess your age (the closer they get, the more they win). At the end of the event, you have the option to see people's guesses. Do you want to learn how old people guessed that you are?

11) You have just participated in a psychological study in which all of the participants rate others' attractiveness. The experimenter gives you an option to see the results for how people rated you. Do you want to know how attractive other people think you are?

12) Some people seek out information even when it might be painful. Others avoid getting information that they suspect might be painful, even if it could be useful.How would you describe yourself?

13) If people know bad things about my life that I don't know, I would prefer not to be told. **[R]**

— APPENDIX B —

Five Facet Mindfulness Questionnaire

Please indicate how true the below statements are of you using the scale provided. [Choices: Never or very rarely true; Rarely true; Sometimes true; Often true; Very often or always true. “R” is scored in reverse. *Observing* items: 1, 6, 11. *Describing* items: 2, 7, 12. *Acting with awareness* items: 3, 8, 13. *Non-judging* items: 4, 9, 14. *Non-reacting* items: 5, 10, 15.]

1) When I take a shower or a bath, I stay alert to the sensations of water on my body.

2) I’m good at finding words to describe my feelings.

3) I don’t pay attention to what I’m doing because I’m daydreaming, worrying, or otherwise distracted. **[R]**

4) I believe some of my thoughts are abnormal or bad and I shouldn’t think that way. **[R]**

5) When I have distressing thoughts or images, I “step back” and am aware of the thought or image without getting taken over by it.

6) I notice how foods and drinks affect my thoughts, bodily sensations, and emotions.

7) I have trouble thinking of the right words to express how I feel about things. **[R]**

8) I do jobs or tasks automatically without being aware of what I’m doing. **[R]**

9) I think some of my emotions are bad or inappropriate and I shouldn’t feel them. **[R]**

10) When I have distressing thoughts or images I am able just to notice them without reacting.

11) I pay attention to sensations, such as the wind in my hair or sun on my face.

12) Even when I’m feeling terribly upset I can find a way to put it into words.

13) I find myself doing things without paying attention. **[R]**

14) I tell myself I shouldn’t be feeling the way I’m feeling. **[R]**

15) When I have distressing thoughts or images I just notice them and let them go.

— APPENDIX C —

Perceived Stress Scale

The questions below ask about your feelings and thoughts during the last week. For each question, you will be asked to indicate how often you felt or thought a certain way. Although some of the questions are similar, there are differences between them and you should treat each one as a separate question. The best approach is to answer each question fairly quickly. That is, don't try to count up the number of times you felt a particular way, but rather indicate the alternative that seems like a reasonable estimate. [Choices: Never; Almost never; Sometimes; Fairly often; Very often. "R" is scored in reverse.]

1) In the last week, how often have you been upset because of something that happened unexpectedly?

2) In the last week, how often have you felt that you were unable to control the important things in your life?

3) In the last week, how often have you felt nervous and stressed?

4) In the last week, how often have you felt confident about your ability to handle your personal problems? **[R]**

5) In the last week, how often have you felt that things were going your way? **[R]**

6) In the last week, how often have you found that you could not cope with all the things that you had to do?

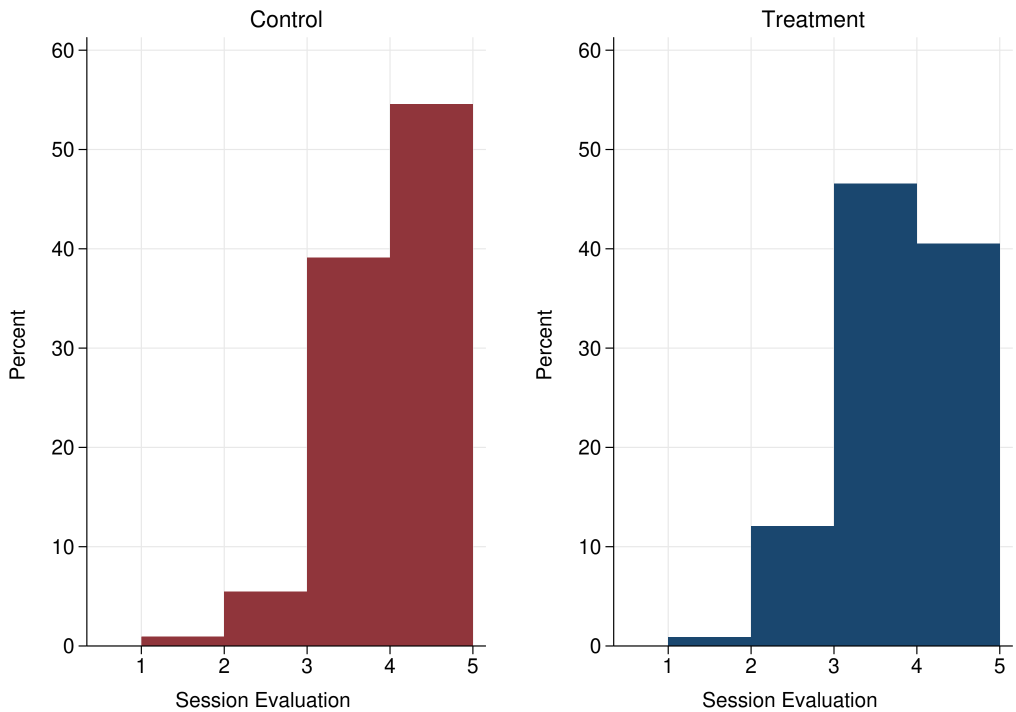
7) In the last week, how often have you been able to control irritations in your life? **[R]**

8) In the last week, how often have you felt that you were on top of things? **[R]**

9) In the last week, how often have you been angered because of things that happened that were outside of your control?

10) In the last week, how often have you felt difficulties were piling up so high that you could not overcome them?

Figure: Average Session Evaluation



Notes: This figure shows the distributions over participants of their average session evaluation during the interventions. The bins are of width 1.

Measuring National Happiness with Music*

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Abstract

We propose a new measure for national happiness based on the emotional content of a country's most popular songs. Using machine learning to detect the valence of the UK's chart-topping song of each year since the 1970s, we find that it reliably predicts the leading survey-based measure of life satisfaction. Moreover, we find that music valence is better able to predict life satisfaction than a recently-proposed measure of happiness based on the valence of words in books (Hills et al., 2019). Our results have implications for the role of music in society, and at the same time validate a new use of music as a measure of public sentiment. *JEL: N30, Z11, Z13*

Keywords: subjective wellbeing, life satisfaction, national happiness, music information retrieval, machine learning.

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[¶]***My Contribution:*** Tuckwell was the lead investigator of this paper.

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1 Introduction

One of the most fundamental human concerns, happiness, has also become a key focus of policymakers, who have recognised its positive effects for health and productivity as well as individual quality of life. Measuring happiness at the macro level is therefore an important area of research, with the most popular method in recent decades being surveys of subjective wellbeing. Recently, in response to historical gaps in such survey data, a new measure was developed which utilised the psychological valence of the words in books (Hills et al., 2019). Like language, music can also encode emotional information: it has been described as a “language of the emotions” (Cooke, 1959), with studies demonstrating that different people can recognise the same patterns of emotion in a song (Juslin, 2013). Moreover, it is the emotional experience that music offers that primarily motivates individuals to listen to it (Juslin and Laukka, 2004). This paper demonstrates that the valence of a country’s most popular songs (extracted using techniques from music information retrieval) can also be used to measure national happiness and can be more robust than a text-based measure.

Our focus for this study is the UK, for which we constructed a Music Valence Index (MVI) using the valence of the most popular song of each year since the 1970s (according to the official music charts). This valence was predicted by a machine learning model (Support Vector Regression) that had been trained to learn audio features associated with high/low valence according to a separate set of songs that had been annotated by human subjects (Soleymani et al., 2013). We find that the MVI displays a significant degree of similarity with the survey-based measure of life satisfaction. First, the MVI appears to mirror key aspects in life satisfaction’s variation over time. Second, the two have a significant pairwise correlation, which persists after controlling for GDP, the effect of time and a battery of other controls. Finally, in a horse race between the MVI and the Text Valence Index (TVI) of Hills et al. (2019), the MVI emerges as a stronger predictor of life satisfaction.

The rest of the paper is organised as follows. Section 2 reviews the relevant literature. Section 3 describes the data. Section 4 presents the results. Section 5 wraps up and offers some final thoughts.

2 Literature

First, our paper relates to the literature in economics that tries to measure happiness. Many papers have discussed the validity of self-reports of subjective wellbeing as a measure, which on the whole are fairly reliable (Diener et al., 2018). Mentioned already is the paper of Hills et al. (2019), whose TVI measure (based on the valence of words in books) is discussed in more detail and compared with the MVI below. To the best of our knowledge, we are the first paper to use measured emotions in music to make any sort of inference about national mood (including happiness).

Second, our work also relates to a literature on the relationship between music and emotions. The fact that over a hundred studies report that different listeners can hear the same emotions in a song illustrates music's potential to express emotions (Juslin, 2013). It therefore stands to reason that listeners might choose songs based on their emotional content to help them work through their own emotions. Indeed, previous work shows how music is used to assist with the emotional processing of significant events, to heighten or strengthen the emotional significance of an activity or ritual, and to manage mood (Sloboda and Juslin, 2010). Our results add to this evidence base by showing that the emotions in the most popular songs reflect how people are actually feeling in the population. The psychology of music literature distinguishes between perceived and induced emotions, and it is important to emphasise that the MVI relates only to perceived emotions; however, this makes it consistent with the notion of music, like a language, being able to describe an emotion to the listener. Whether or not the music has an emotional impact on the listener is therefore not gauged by the MVI (and of course we make no claim that popular music is actually affecting national happiness), but our results (and our success in developing a measure of national valence) support the idea that the emotional content of popular music reflects the expressed emotions of listeners. We remain agnostic as to the cause, but one idea could be that people are more likely to buy a record if it is in tune with how they are feeling, which would imply that the most popular record is then the one that is best able to capture the public mood; this is at least consistent with additional evidence (presented in Appendix A) which demonstrates that the chart topping song is better able to capture national happiness than tracks further down the charts that are less popular. Note, such a process could be further facilitated by record labels, who would be motivated to promote tracks and artists that tap the public mood if such a strategy is favourable to selling records (indeed, Hills et al. (2019) suggest a similar mechanism for the TVI in relation to publishing houses and books).

Finally, our paper relates to the data science literature on music emotion recognition, a branch of music information retrieval (Kim et al., 2010). We provide a new application of these methods: correlating the emotions extracted with socio-economic variables.

3 Data

3.1 Music Valence

3.1.1 Popular Music

We identified the most popular song of the year in the UK using the official singles chart (www.officialcharts.com), which is based on record sales. Only weekly charts are available before 2005 so we applied the following transformation to determine annual scores. Let x_i be a track's chart position in a given week (1st, 2nd, etc.) and y be the lowest possible position on the weekly chart during the year (e.g. 50th, 100th); a track's popularity score for that year would be calculated as $\sum_{i=1}^{52}(y+1-x_i)$, with the highest-scoring then selected as the most popular. Note, it could be the case that people buy more music during certain weeks of the year (e.g. around Christmas time), so the track we identify as most popular might not have actually obtained the most record sales during the year; rather, the score picks up songs which had lasting popularity over the whole year. The most popular songs were then purchased from Amazon Music or the Apple iTunes Store depending upon availability (the song list is available in Appendix B, along with each song's predicted valence).

3.1.2 Valence Prediction

To predict the valence scores of each song we trained a machine learning model to learn audio features that best predicted valence using a separate set of tracks that had been annotated by human subjects. The annotated dataset comes from Soleymani et al. (2013) (http://cvml.unige.ch/databases/emoMusic/). It consists of 45-second clips of 744 songs from the Free Music Archive (https://freemusicarchive.org/) that span a variety of popular genres (blues, electronic, rock, classical, folk, jazz, country, pop). Each clip was annotated by a minimum of 10 participants on a 9-point valence scale, the average of which is our target measure. We computed our own audio features (191 in total) using the 45-second clips (details are provided in Appendix C). Because the valence target exists on an approximately continuous scale (after averaging across participants), we use a regression framework for prediction. Specifically, we use a Support Vector Regression (SVR) which has displayed relatively good performance for predicting valence in comparison to other regression methods (Yang et al., 2008).

To arrive at our predictive model, we first used a 5-fold cross validation procedure to optimise the SVR algorithm's parameters and the number of features (using R^2 to assess performance on the validation sets). We then trained a model using a fraction ($619 \approx 83\%$) of the annotated songs and tested its performance on the remaining 125 songs to see how well it might generalise; we were able to achieve a reasonably high R^2 on the test set in comparison to machine learning methods from other papers (0.33). Note that we used the same train-test split as in Soleymani et al. (2013) so we could benchmark the model's performance. Finally, we re-trained the model on the full sample of 744 annotated songs and used it to predict the valence scores of the UK's most popular songs (using 45-second clips extracted from the middle of each song as input data), which generates what we call the MVI.

3.2 Other Happiness Measures

3.2.1 Life Satisfaction

To validate the MVI, we use Eurobarometer life satisfaction data (the average per year of all individuals surveyed). This is the longest-running measure of subjective wellbeing (available since 1973), and is also the one used to validate the TVI in Hills et al. (2019). The question asked is, "On the whole, are you very satisfied, fairly satisfied, not very satisfied, or not at all satisfied with the life you lead?", with responses given on a 4-point Likert scale.

3.2.2 Text Valence

The TVI measure from Hills et al. (2019) was constructed using the Google Books corpus (Lin et al., 2012). They derived annual valence scores for the UK using the average valence of words in books published in Great Britain during a particular year (weighted by their word frequencies). The valence norms used were for 14,000 English words (each an average of valence ratings by 20 participants on a 9-point scale (Warriner et al., 2013)).

3.3 Controls

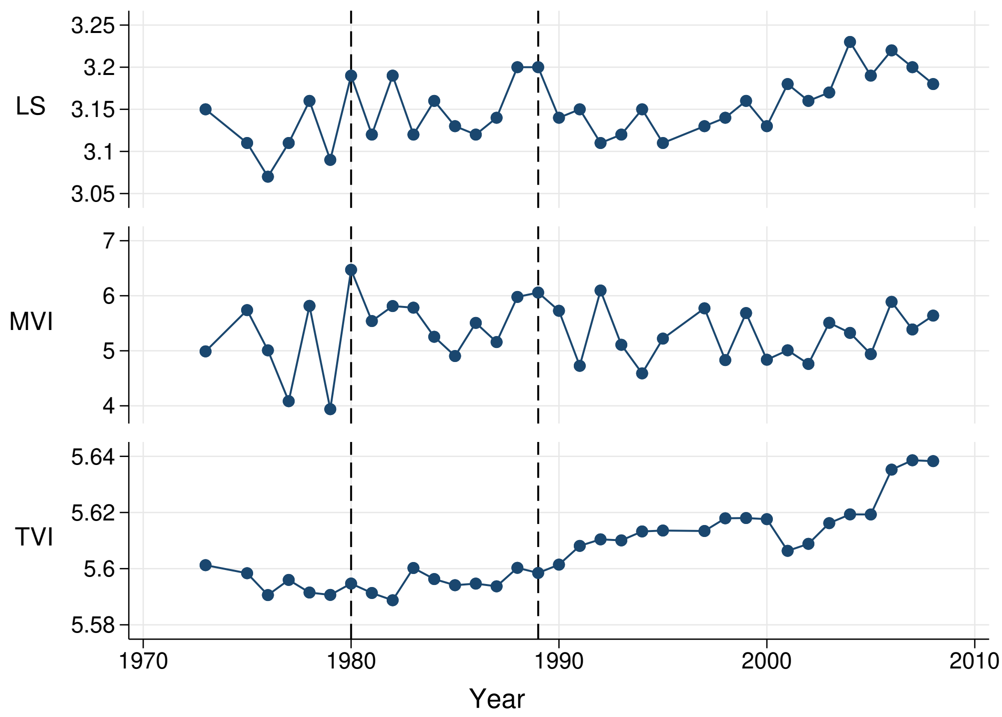
Incorporated in the analyses below are traditional controls used in the subjective wellbeing literature. Firstly, our measure of GDP is from the Penn dataset (in 2005 international dollars, adjusted for purchasing power parity). We also use a set of measures from the OECD: life expectancy at birth (as a measure of health); education inequality (measured as a GINI index); total gross central government debt as a percentage of GDP (as a measure of public expenditure); and inflation.

4 Results

4.1 Time Series of Life Satisfaction, MVI and TVI

As seen in Figure 1, the MVI displays a high degree of similarity with life satisfaction over time, mirroring key elements in its variation. For example, local peaks in life satisfaction in 1980 and 1989 are picked up by the MVI, which also appears to match well the frequency of the life satisfaction data. The TVI on the other hand does less well at picking up such peaks, with its frequency resembling that of a smoothed series. These "eyeballing" observations are confirmed by formal statistical analysis, to which we will now turn.

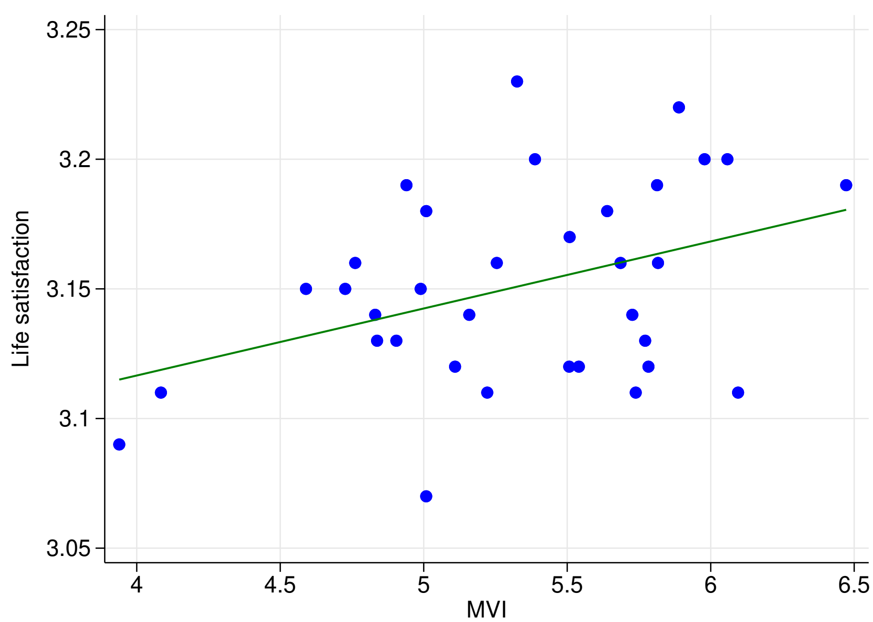
Figure 1: Time Series of Life Satisfaction (LS), MVI and TVI



4.2 Correlation of Life Satisfaction and MVI

Figure 2 shows a scatter plot of life satisfaction and the MVI. As can be seen, they display a significant positive correlation ($r = 0.39$; $p = 0.02$).

Figure 2: Scatter Plot of Life Satisfaction and MVI



The analysis in Table 1 then shows that this positive relationship between MVI and life satisfaction is robust to the introduction of GDP, a time trend and various other controls ($p = 0.003$ without the additional controls; $p = 0.008$ with them). In all regression analyses we report (White) standard errors that are robust to heteroskedasticity, but there are no substantive differences in the results with regular standard errors.

Table 1: The MVI Predicts Life Satisfaction

Marginal effects	Life satisfaction	
	(1)	(2)
MVI	0.392^{***} (0.122)	0.388^{***} (0.135)
GDP	6.645^{*} (3.828)	6.840 (4.700)
Trend	Yes	Yes
Other controls	No	Yes
Observations	34	34

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Marginal effects with robust (White) standard errors in parentheses. Life satisfaction and MVI are standardised; GDP is the logarithm of gross domestic product per capita. Other controls include life expectancy, education inequality, public debt and inflation.

4.3 Comparing the MVI and TVI

As shown in Table 2, when included in the same regression, the MVI emerges as a stronger predictor of life satisfaction than the TVI for the UK, with only its coefficient remaining significant. This holds true whether the full set of controls (life expectancy, education inequality, public debt and inflation) are included or not ($p = 0.004$ without the additional controls; $p = 0.007$ with them).

Table 2: MVI a Stronger Predictor of Life Satisfaction than the TVI

Marginal effects	Life satisfaction	
	(1)	(2)
MVI	0.394*** (0.125)	0.405*** (0.139)
TVI	-0.099 (0.236)	-0.276 (0.347)
GDP	6.677* (3.861)	6.666 (4.642)
Trend	Yes	Yes
Other controls	No	Yes
Observations	34	34

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$. Marginal effects with robust (White) standard errors in parentheses. Life satisfaction, MVI and TVI are standardised; GDP is the logarithm of gross domestic product per capita. Other controls include life expectancy, education inequality, public debt and inflation.

5 Discussion

In this paper we have provided evidence that the valence of a country's most popular songs can provide a reliable indication of average happiness in the population. Moreover, for the UK at least, it appears that the valence of popular music provides a more accurate depiction of its happiness than the valence of books, which supports the idea of music as a specialised "language of the emotions" (Cooke, 1959). A nice feature of the measure is that it only requires collecting information on one song each year (the most popular), which makes it relatively cheap and easy to implement. We support this further in Appendix A where we show that using the valences of tracks that are less popular (including an average of the top 10 songs) does not work as well as focusing only on chart-topping songs.

Here we have only shown that music can predict happiness within a country. Future research might wish to consider the potential of music to explain between-country differences in happiness. Music has the potential to be a good between-country predictor since it is not only an emotional language, but a "universal" one (Longfellow, 1835) and is found in every society with a stable set of functions (Mehr et al., 2019). In general, we hope to encourage a closer look at the emotions in music as potentially representative of underlying social and cultural patterns.

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Table: The Most Popular Song is the Best Measure of Life Satisfaction

Correlations *(p)*	Life Satisfaction
Valence of #1 Song (MVI)	0.386** (0.024)
Valence of #2 Song	0.128 (0.471)
Valence of #3 Song	0.235 (0.180)
Valence of #4 Song	0.344* (0.054)
Valence of #5 Song	-0.161 (0.364)
Valence of #6 Song	0.022 (0.902)
Valence of #7 Song	0.017 (0.924)
Valence of #8 Song	-0.157 (0.375)
Valence of #9 Song	0.308* (0.077)
Valence of #10 Song	0.017 (0.924)
Average Valence of #1-#10 Songs	0.307* (0.077)

Pairwise correlations with p-values in parentheses. Statistically significant measures presented in bold: $^{**}p < 0.05$; $^{*}p < 0.1$.

Table: Most Popular Songs of the Year and their Predicted Valences (which form the MVI)

Year	**Title**	**Artist**	**Valence** *(1-9)*
1973	Tie a Yellow Ribbon Round the Ole Oak Tree	Dawn featuring Tony Orlando	4.99
1974	The Wombling Song	The Wombles	5.40
1975	Bye Bye Baby	Bay City Rollers	5.74
1976	Mississippi	Pussycat	5.01
1977	Evergreen	Barbra Streisand	4.08
1978	Rivers of Babylon	Boney M.	5.82
1979	Bright Eyes	Art Garfunkel	3.94
1980	Feels Like I'm in Love	Kelly Marie	6.47
1981	Birdie Song	The Tweets	5.54
1982	Come On Eileen	Dexy's Midnight Runners	5.81
1983	Blue Monday	New Order	5.78
1984	Relax	Frankie Goes To Hollywood	5.25
1985	The Power of Love	Jennifer Rush	4.90
1986	So Macho	Sinitta	5.51
1987	Never Gonna Give You Up	Rick Astley	5.16
1988	Push It	Salt-N-Pepa	5.98
1989	Ride on Time	Black Box	6.06
1990	Killer	Adamski	5.73
1991	(Everything I Do) I Do It for You	Bryan Adams	4.73
1992	Rhythm Is a Dancer	Snap!	6.10
1993	No Limit	2 Unlimited	5.11
1994	Love Is All Around	Wet Wet Wet	4.59
1995	Think Twice	Celine Dion	5.22
1996	Return of the Mack	Mark Morrison	5.98
1997	I'll Be Missing You	Puff Daddy & Faith Evans	5.77
1998	How Do I Live	LeAnn Rimes	4.83
1999	Heartbeat	Steps	5.69
2000	Amazed	Lonestar	4.84
2001	Whole Again	Atomic Kitten	5.01
2002	How You Remind Me	Nickelback	4.76
2003	In Da Club	50 Cent	5.51
2004	Left Outside Alone	Anastacia	5.33
2005	You're Beautiful	James Blunt	4.94
2006	Hips Don't Lie	Shakira featuring Wyclef Jean	5.89
2007	How to Save a Life	The Fray	5.39
2008	Rockstar	Nickelback	5.64
2009	Poker Face	Lady Gaga	6.01
2010	Empire State of Mind	Alicia Keys	4.45

Valence Prediction

We extracted commonly used acoustic features for music emotion recognition (Kim et al., 2010) using the music processing libraries Librosa (McFee et al., 2015) and Essentia (Bogdanov et al., 2013):

- Spectral Centroid
- Spectral Rolloff
- Spectral Contrast - 7 bands
- Mel-Frequency Cepstrum Coefficients (MFCC) - 24 coefficients
- Zero Crossing Rate
- Chroma Energy Normalized Statistics (CENS) - 12 chroma
- Beat Per Minute (BPM)
- Root Mean Square (RMS)
- Spectral Flux
- Onset Rate
- High Frequency Content (HFC)

All features were extracted at the frame level except for BPM, RMS, spectral flux, onset rate and HFC. For frame-level features, we used Hann windows of 46 ms, and computed the mean and variance of the frame values and first-order differences. In total there were 191 features.

We then trained a Support Vector Regression (SVR) on the annotated Free Music Archive dataset using radial basis functions as kernels. Features were preprocessed with z-score normalisation (removing the mean and scaling to unit variance) so features with large magnitude would not dominate the objective function. A 5-fold cross-validation procedure selected the optimal parameters of the SVR algorithm and number of features (100). Feature selection was carried out using the F-test which tests the individual effect of each feature by converting the correlation between each feature and the valence to an F score. Using the same train-test split as in Soleymani et al. (2013), our achieved R^2 on the test set compares favourably with other machine learning models:

Method	Valence R^2
This Paper	0.33
Baseline[a]	0.12
MFCC[b]	0.20
TUM[c]	0.42
UAizu[c]	0.35
UU[c]	0.31

[a] Soleymani et al. (2013). [b] Choi et al. (2017). [c] Soleymani et al. (2014).